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ADAPTIVE CLUSTER SAMPLING OF GULF OF ALASKA ROCKFISH

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ADAPTIVE CLUSTER SAMPLING OF GULF OF ALASKA ROCKFISH

A

THESIS

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Abstract

National Marine Fisheries Service trawl surveys result in more variable biomass estimates for long-lived Gulf of Alaska rockfish than researchers expect. Adaptive cluster sampling (ACS) was investigated to improve these surveys. In August 1998 east of Kodiak, AK, a sampling cruise tested ACS for Pacific ocean perch (POP), and shortraker and rougheye rockfish (SR/RE). In each of six strata, simple random sampling was conducted, then ACS was performed on top stations. Stopping rules prevented sampling from continuing indefinitely. Results did not resolve whether ACS alone was better than simple random sampling. ACS, combined with stratification, increased precision of POP estimates by 30% over random sampling, suggesting that the spatial distribution has both fine-scale and habitat-scale patterns. Variograms indicated that the expected aggregation was not encountered for POP, but that POP are more aggregated than SR/RE. Some diel movement of POP was evident. Both species were concentrated at specific depths.

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Introduction

The assessment of fish populations is one of the most important, but problematic, areas in fisheries management. Assessing slope rockfish (*Sebastes*) species in the Gulf of Alaska and elsewhere has been particularly difficult. Investigating alternative survey designs for estimating rockfish biomass has become central in managerial concerns. This thesis investigates a relatively new sampling design, adaptive cluster sampling, for its potential use on three slope rockfish species.

The slope rockfish assemblage in the Gulf of Alaska (GOA) is a group of species that includes Pacific ocean perch (*Sebastes alutus*), rougheye rockfish (*S. aleutianus*), shortraker rockfish (*S. borealis*) and several others. This thesis focuses on the Pacific ocean perch (POP hereafter) and shortraker and rougheye rockfish (SR/RE hereafter) treated together.

POP is the dominant and most commercially important rockfish species in the GOA. They are usually found between depths of 100-450 m. Adult maximum size is ~45 cm and maximum age is between 30 and 77 years with natural mortality estimated at 0.05. POP mature at 4-13 years for males and 5-15 years for females (DiCosimo 1998). Adult POP migrate into deep water during fall to spawn and move to shallower depths to feed in spring. Major prey groups include euphausiids, pandalid shrimps and squid (Balsiger et al. 1985, DiCosimo 1998).

Although the stock is managed for different regions, genetic research has shown little distinct geographic variation among the species (Gunderson and Seeb 1988). Genetic research currently underway may indicate otherwise (A.J. Gharrett 2000, University of Alaska Fairbanks, Juneau Center, School of Fisheries and Ocean Sciences, 11120 Glacier Hwy, Juneau AK 99801, *personal communication*). A foreign trawl fishery on this species started in the early 1960's and had a peak catch of about 350,000 mt in 1965. Large catches in the 1960's led to a major stock decline that has only recently been reversed. This reversal was likely due to some of the large recent year classes and because the fishery has been a domestic fishery since 1985 and managed under conservative catch limits (Heifetz et al. 1994). Recent (1998) acceptable biological catch (ABC) set by the North Pacific Fishery Management Council (NPFMC) was 12,820 mt and total allowable catch (TAC) at 10,776 mt with catch taken primarily by trawler (Witherell 1999).

SR/RE rockfish are the larger, deeper-water commercial counterparts to the POP. They grow larger (up to 110 cm for SR), live longer (up to 125 years) and swim deeper (over 1000 m). Natural mortality is estimated at 0.025 for RE and 0.03 for SR (DiCosimo 1998). Historically, bottom trawls have targeted the majority of the catch, but now the entire TAC is required for bycatch in trawl and longline fisheries. The TAC is set equal to the ABC for SR/RE and is only about one-tenth that of POP (1590 mt, Dicosimo 1998) with 70% allocated to trawl gear and 30% to fixed gear. While the POP estimates have fluctuated widely in the last six surveys, the SR/RE have stayed between 56,000-86,000 mt (Heifetz et al. 1999) with much tighter (20% the relative width) confidence intervals [(52,211-83,564 mt) in 1999]. This may be due to a uniform distribution of SR/RE when compared to the highly aggregated distribution of POP (Lunsford 1999).

National Marine Fisheries Service (NMFS) scientists have surveyed rockfish biomass triennially since 1984 (Heifetz et al. 1999). Current assessment of POP in the Gulf of Alaska is challenging to scientists because of the extremely wide confidence intervals of the biomass estimates. A stock-synthesis model incorporates these biomass estimates to provide estimates of population parameters (Heifetz et al. 1994, 1995, 1996). The model describes the population dynamics of an age-and-length-structured population (Quinn and Deriso 1999). Heifetz et al. (1994) showed that survey age composition is in accord with fishery catch-per-unit effort (CPUE) data, fishery catch composition and survey catch composition but survey biomass is not. Between-survey biomass estimates are unusually variable for a long-lived species and the fluctuations are greater than can be explained by survey measurement error alone (Table 1). In the stock synthesis model, this problem is dealt with by giving survey biomass low weight in comparison to other data sources. The result is that estimated biomass approximates average survey biomass, but that survey biomass in any one year can differ from estimated biomass by a significant amount.

Table 1. Pacific ocean perch (POP) survey biomass estimates from 1984-1999 from the National Marine Fisheries Service triennial survey.

Year	Biomass (mt)	95% Confidence Interval
1984	232,694	101,550 – 363,838
1987	214,827	125,499 – 304,155
1990	138,003	70,993 – 205,013
1993	460,755	255,253 – 665,987
1996	778,663	358,923 – 1,198,403
1999	726,785	0 – 1,156,111

Other concerns expressed about the trawl surveys (Rockfish Working Group 1991; ADF&G memo included in Heifetz et al. 1995) include:

1) The Gulf-wide survey is designed to provide information about all groundfish species, and survey effort is evenly distributed across the Gulf. Sampling effort is allocated to various depth and area strata to minimize the variance of total groundfish biomass. However, this design may not be appropriate for assessing POP and other slope rockfish, because their distributions may not be well sampled by this uniform design.
2) The distribution of POP is clustered, so that survey estimates of abundance are highly variable.
3) The continental slope where many rockfish species are found is narrow and makes up a small part of the total area. Hence, the slope is likely under-sampled with regard to slope rockfish populations.

These agency concerns have led to the need to look at alternative sampling designs. For aggregated populations like the POP, the most promising is adaptive cluster sampling (ACS).

Adaptive sampling is a relatively new area of sampling design. The central theme of all adaptive designs is the inclusion of the ability to change the way the survey is conducted as the variable of interest is observed. The particular adaptive design focused on here is adaptive cluster sampling. This design was created for sampling rare or clustered species. In the case of rockfish, rare is in the sense that most portions of the GOA contain few, but some areas contain many. In ACS, an initial sample is selected and whenever the variable of interest (fish abundance in this case) exceeds some condition, the area is sampled more intensely.

Steven Thompson first introduced ACS to sample rare species of Hawaiian birds (Thompson and Ramsey 1983). Thompson added more theory in a sampling theory book (Thompson 1992), a book dedicated to adaptive sampling (Thompson and Seber 1996), and several papers in the literature (see below). Over the last 15 years, there has been an eruption of various adaptive sampling designs (Francis 1984, Gasaway et al. 1986, Hiby and Hammond 1989, Jolly and Hampton 1990, Roesh 1993, Danaher and King 1994, Englund and Herari 1995, Smith et al. 1995). These designs have focused on areas of study such as whales, moose, hardwood trees and household attributes. Until recently, only a few designs have been directed towards fisheries problems, even though many commercially important fishes exhibit aggregated patterns that make conventional designs inefficient. One application was a restricted adaptive design sampling larval fish that was conducted in California (Lo et al. 1997), which resulted in a great improvement in precision of the survey. The tradeoff was that an unknown amount of bias was induced due to stopping rules. Many papers in the recent literature have shown that ACS can be effective on clustered populations (Thompson 1990, 1991a, b, 1992, Smith et al. 1995, Thompson and Seber 1996).

In the last several years there have been studies of ACS that focused on simulations and modifying previous ACS designs (Christman 1997, Brown and Manly 1998, Su and Quinn (University of Alaska Fairbanks, Juneau Center, School of Fisheries and Ocean Sciences, 11120 Glacier Hwy, Juneau AK 99801, *unpublished work*). Salehi and Seber (1997a,b) and Salehi (1999) have produced several papers recently that provide a more theoretical basis for different adaptive cluster designs. Some of the promising results from the recent literature have led to further exploration of this design on rockfish populations in the Gulf of Alaska.

A pilot study in 1996 collected data for evaluating adaptive sampling designs for POP (Clausen and Heifetz 1996). An exploratory phase consisted of making tows to find stations with varying densities of POP and then intensive sampling was conducted around selected stations. There were three clusters of observations. Two of these had low densities of about the same magnitude, while one had a wide range of densities from low to high. A simulated population was constructed using these samples, and adaptive cluster sampling reduced the estimated variance up to 50%, suggesting that adaptive cluster sampling would be effective for rockfish populations (Quinn and Haldorson 1997).

Based on this work, an adaptive cluster sampling experiment was conducted in 1998 in a small area of the Gulf of Alaska (Figure 1). The main hypothesis was that ACS would provide more precise estimates of POP biomass than would a simple random survey design. A secondary hypothesis was that assessment of POP abundance would benefit more from an ACS design than would SR/RE rockfish, because it is believed that POP are more clustered in their distribution than SR/RE rockfish. SR/RE are treated together because they are managed as a species complex by the NPFMC. This thesis summarizes the results from this experiment and evaluates these two hypotheses.

Another important consideration of whether an ACS design is worthwhile is how the target species are distributed spatially and temporally. The design used in this study had stopping rules, set sampling distances, and depth strata imposed somewhat arbitrarily, because the interaction of rockfish spatial distributions and ACS had not been looked at in much detail. This thesis analyzes the spatial results in detail to determine if the design took advantage of the spatial distribution of POP and SR/RE and to determine appropriate methods for implementing adaptive cluster sampling on a larger scale. The diel pattern of survey catches is also examined to investigate if the temporal distribution had an effect on sampling.

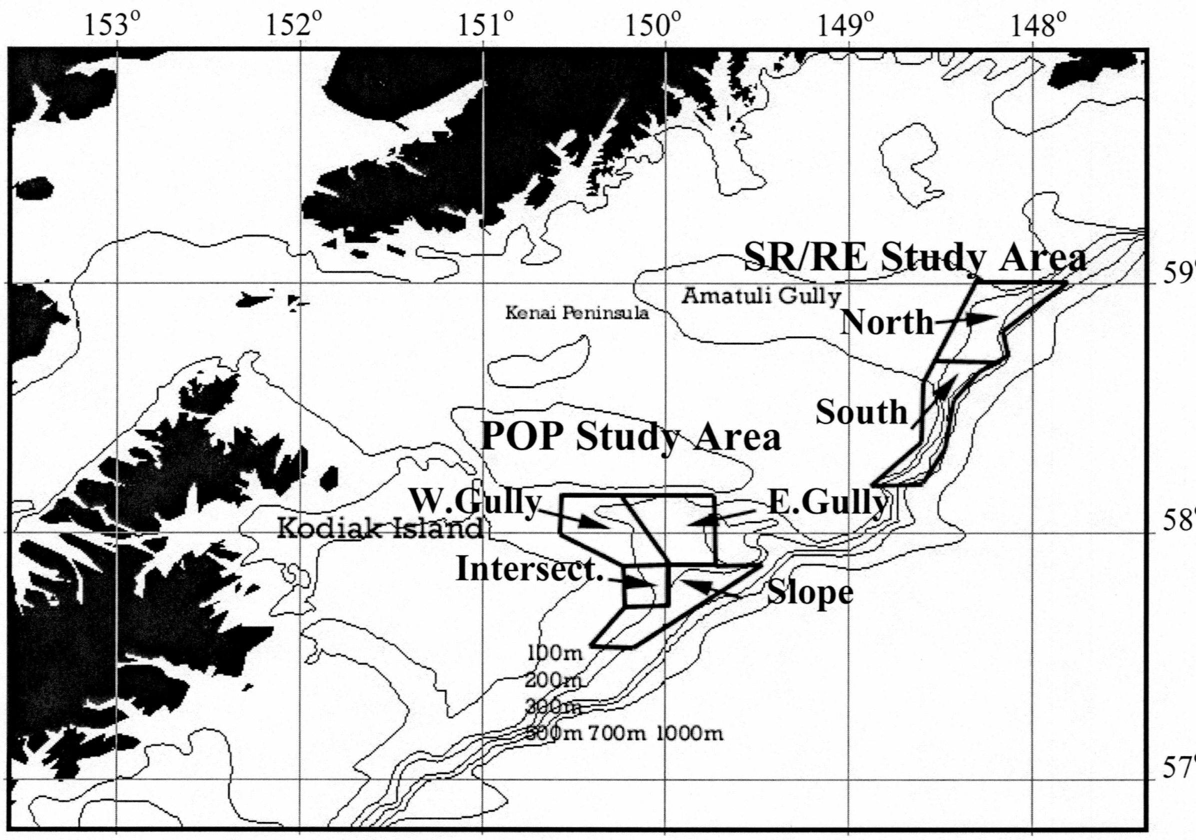

Figure 1. Map of sampling areas in the Gulf of Alaska on the Unimak 98-01 adaptive sampling cruise.

Materials and Methods

Experimental Design

In the basic adaptive cluster sampling method (ACS), a simple random sample (SRS) of size n is taken; if y (the variable of interest) exceeds c (a criterion value), then neighborhood units are added (e.g., units above, below, left, and right in a cross pattern, Figure 2) to the sample. If any neighborhood cell has $y>c$, then its neighborhood is added. This process continues until no units are added or until the boundary of the area is reached (Thompson and Seber 1996, p.93). Neighborhoods can be defined in any general way. The only condition is that if unit i is in the neighborhood of j, then unit j is in the neighborhood of i. The unbiasedness of the estimators relies on all neighborhood units of $y>c$ being sampled. If logistics cause the sampling to be curtailed before the sampling is complete, then biased estimators can result.

In adaptive cluster sampling with order statistics (ACSORD), the adaptive sampling is based on the order statistics of the initial SRS (Thompson and Seber 1996, p.160-1; chapter 6). An initial SRS of size n is taken, producing an ordered list of sample values

$$y_{(1)} \le y_{(2)} \le \ldots \le y_{(n-r)} \le y_{(n-r+1)} \le \ldots \le y_{(n)},$$

where $y_{(1)}$ is the lowest value and $y_{(n)}$ is the highest. An adaptive sampling phase is then carried out in the neighborhoods of the top r sample units whose y-values are greater than the criterion value $c = y_{(n-r)}$. The adaptive sampling phase forms r clusters consisting of sampling units that exceed the criterion value c and boundary units called edge units that do not exceed c. A network is further defined to be a cluster with its edge units removed.

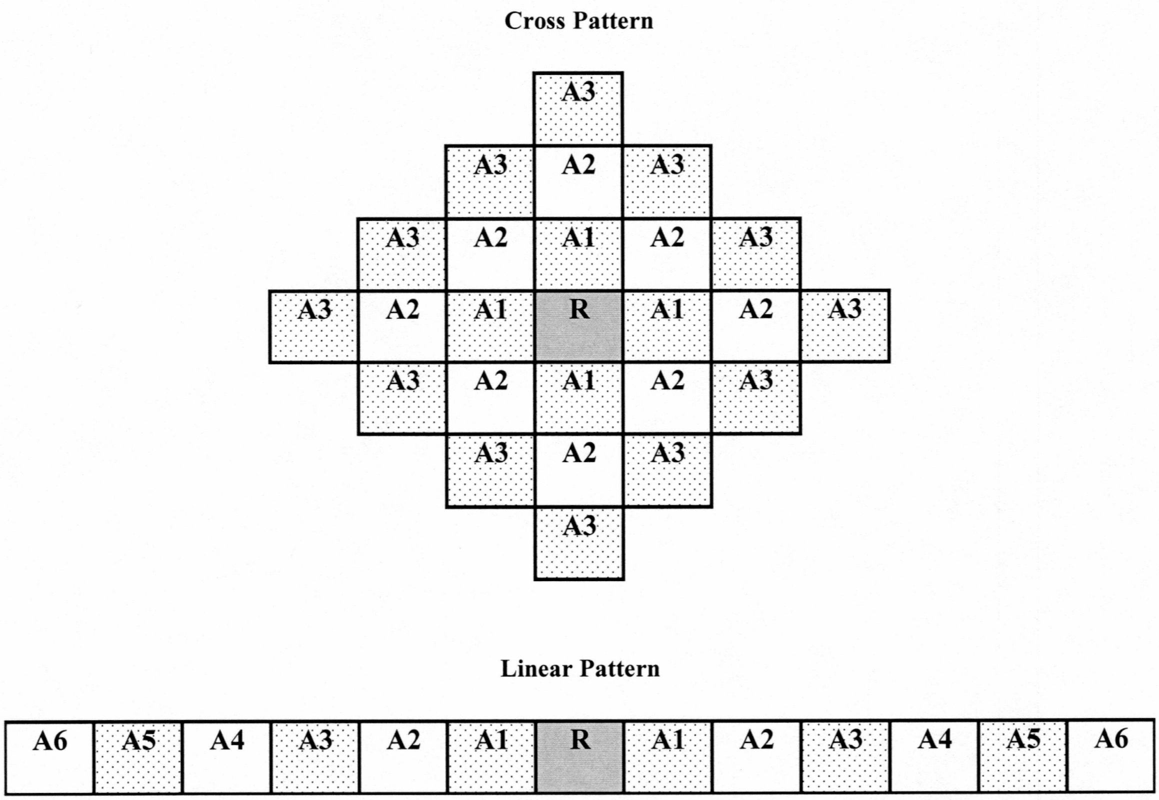

Figure 2. Maximum possible number of adaptive hauls for the cross (stopping rule of 3) and linear (stopping rule of 6) patterns with the imposition of a stopping rule. The initial random station is denoted as "R," and the adaptive stations as "A" and their respective level number.

In August 1998, ACS was conducted in six strata near the Portlock Bank in the Gulf of Alaska (Figure 1, p.7), four for POP and two for SR/RE. The POP area was chosen for two reasons: (1) in recent years it has generally been a location of high catches of POP in the commercial fishery, and (2) it covers an area of variable topography that includes both the upper continental slope and a gully extending into the continental shelf, thereby providing a range of possible habitats for POP. The POP strata corresponded to summer preference of depths between 150-300 m, while the SR/RE strata were in depths between 300-500 m. A 182 ft. factory trawler, the Unimak Enterprise (now called only

Unimak), was chartered on a cost-recovery basis to conduct trawl samples. The nets and codend used were the same as used in the triennial survey with roller gear designed for rocky bottom terrain. The trawl doors and rigging apparatus were provided by the trawler. A detailed description of the gear is presented in Clausen et al. 1999. Fishing operations were conducted 24 hours a day. No attempt was made to account for possible day-night differences in catch rates; this factor was examined *a posteriori*. Duration of all trawl hauls was 15 minutes on bottom, measured from the time the net reached equilibrium on the bottom until the time that retrieval of the net began. Fifteen minutes was chosen to correspond with the standard duration of hauls during the triennial trawl surveys. Each haul covered a tow length of about 1.7 km (0.9 nm). Tows were made parallel to the depth contours. The latitudes and longitudes for the initial station positions were chosen in the six strata by using a random number generator. Once the starting point was reached, a coin flip was planned to determine the direction along the contour to be towed (east-west for POP, north-south for SR/RE). The variable of interest was catch-per-unit-effort (CPUE), which was the weight of target species (kg) divided by the length towed (km). This measurement is assumed a reasonable proxy for density (biomass/unit area).

Each stratum was sampled initially with 12–15 randomly located stations (trawl hauls). In each stratum, after random sampling was completed, the experiment switched to an adaptive sampling phase. In this mode, a series of additional hauls in each stratum was made systematically around a selected number (r) of the random stations with the highest CPUE of the target species. For the shortraker-rougheye study area, the target species CPUE was for shortraker and rougheye rockfish combined. The value of r was initially set to three, so that the fourth largest CPUE became the criterion value for adaptive sampling. In the west gully, east gully and intersection strata, ACS was conducted in a cross pattern of four tows around each selected high-CPUE station (Figure 2, p.9). For these strata, the bottom topography required that all samples were towed in a general east-west direction. Consequently, the cross pattern consisted of adaptive tows on the eastern and western sides of each selected random tow (bathymetry-parallel), and tows to the north and south (bathymetry-perpendicular). In the slope and shortraker-rougheye strata, the bathymetry-perpendicular adaptive tows were omitted, resulting in a linear pattern in which adaptive tows were made only east and west of the initial random station (Figure 2, p.9). This linear pattern was necessary because of the steeply sloping bottom in these strata. A distance of 0.19 km (0.1 nm) was planned between the tracks of adaptive tows in all directions to avoid depletion effects on the catches.

A major problem in applying adaptive sampling is that if scientists set too low of a criterion value, then sampling could continue indefinitely. To limit the amount of adaptive sampling, an arbitrary stopping rule of S levels was imposed. For those strata where the cross pattern of adaptive sampling was used, the stopping rule was $S = 3$ levels, allowing for a maximum of 24 adaptive tows around each high-CPUE random station (Figure 2, p.9). For the strata with the linear pattern of adaptive sampling, the stopping rule was $S = 6$ levels, for a maximum of 12 adaptive tows around each high-CPUE random station. In addition, no adaptive sampling extended beyond a stratum boundary. The result of adaptive sampling around each high-CPUE station was a network of tows that extended over and, in some cases, delineated the geographic boundaries of a rockfish aggregation.

Statistical Methods

Adaptive Sampling

Statistical analysis of the results was based on adaptive cluster sampling with order statistics (ACSORD) (Thompson and Seber 1996). Abundance for the targeted rockfish species in each stratum was estimated from the initial random stations. Then, two adaptive estimators of abundance, a Hansen-Hurwitz-like estimator (HH) and a Horvitz-Thompson-like estimator (HT) were calculated. Estimates of standard errors (SEs) and coefficients of variation of the mean (CVs, $\mathrm{SE}/\hat{\mu}$) were computed for each estimator. The HH estimator essentially replaces stations around which adaptive sampling occurred with the mean of the network of adaptive tows that exceeded the criterion CPUE value. The HT estimator is based on the probability of sampling a network given the initial stations sampled and involves the number of distinct networks sampled (in contrast to the HH estimator based on the initial stations). This estimator often outperforms other estimators as seen in simulation studies (Su and Quinn, University of Alaska Fairbanks, Juneau Center, School of Fisheries and Ocean Sciences, 11120 Glacier Hwy, Juneau AK 99801, *unpublished work*). Because subsampling was necessary to obtain estimates of rockfish catches for each haul, the standard estimation formulae were adapted to include within-haul variation (Quinn et al. 1999; see Appendix I).

The unbiased estimator of the mean for SRS is defined as:

(1) $$\hat{\mu}_{SRS} = \frac{1}{n}\sum_{i=1}^{n} y_i ,$$

where y_i is the CPUE value for sample unit i in the initial sample.

An unbiased estimator of the mean, the HH estimator, is defined for ACSORD in Thompson (1996):

(2) $$\hat{\mu}_{HH} = \frac{1}{n}\sum_{i=1}^{n} w_i = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i^*}{x_i} ,$$

where w_i and y_i^* are the mean and total of the x_i observations in the network that intersect sample unit i, respectively. The variance estimate used is the biased, but more practical estimator $\tilde{\text{var}}(\hat{\mu}_{HH})$. Thompson and Seber (1996) state this may be better because it is simpler and is invariably nonnegative.

The HT estimator of the mean (Thompson 1990) takes the form

(3) $$\hat{\mu}_{HT} = \frac{1}{N}\sum_{k=1}^{\kappa} \frac{y_k^*}{\alpha_k} ,$$

where y_k^* is the sum of the y-values for the *k*th network, κ is the number of distinct networks in a sample, and α_k is the probability that network k is included in the sample. If there are x_k units in the *k*th network, then

(4) $$\alpha_k = 1 - \binom{N - x_k}{n} \Big/ \binom{N}{n} .$$

This estimator is design unbiased (the average of all possible samples would yield the exact population parameters) in ACS for a population with distinct networks defined by a constant criterion. In ACSORD, the criterion value changes with each sample, so the estimator is biased and is considered inappropriate (Thompson and Seber 1996) but is presented here for comparative purposes.

When a stopping rule is used, the theoretical basis for adaptive sampling designs changes. This rule may result in incomplete networks that overlap and are not fixed relative to a specified criterion. In contrast, the non-stopping-rule scheme has disjoint networks that form a unique partition of the population for a specified criterion. This partitioning is the theoretical basis for the unbiasedness of $\hat{\mu}_{HH}$. Thus with a stopping rule, not only is $\hat{\mu}_{HT}$ biased, but $\hat{\mu}_{HH}$ is too.

Recent simulation studies (Su and Quinn *unpublished work*) have estimated the bias induced by each of these estimators. Factors examined were the initial sample size, order statistic r and the aggregation of the population. For the HT estimator without a stopping rule under ASCORD, the bias is always positive but small (<10%). Applying a stopping rule of three to the HH estimator resulted in a maximum positive bias of 17% for a highly aggregated population but was lower for an r-value of less than four (as in this survey). When the stopping rule is applied to the HT estimator, its maximum bias is approximately +12% but can be slightly negative at high r-values. From these simulations, a tradeoff of relatively small bias for a gain in precision may be acceptable.

Two hypotheses were evaluated: (1) Adaptive sampling would be more effective in providing precise estimates of POP biomass than would a simple random survey design. (2) Assessment of POP abundance would benefit more from an adaptive sampling design than would SR/RE, because POP are believed to be more clustered in their distribution than SR/RE. SRS estimates were obtained from the initial random stations and standard errors were calculated for the initial sample size and for the same sample size used in the adaptive estimates. These hypotheses will be assessed by comparing the standard errors (SEs) and coefficients of variation (CVs) of ACS to SRS. Substantial reductions in these statistics using ACS compared to SRS for POP would support the first hypothesis, whereas no gains in precision using ACS compared to SRS for SR/RE would support the second hypothesis. This comparison is qualitative because relevant significance tests are unavailable and the two methods are different in terms of logistical efficiency.

Stratification

The intersection and the two gully strata, which were the POP strata sampled with a cross pattern, were combined into a single area, in order to explore the effects of stratification and adaptive sampling on the precision of the estimates. First, the data from the initial random stations from the combined areas were treated as a simple random sample, since the strata were of similar size. Next, the combined area was analyzed as if it were a stratified random sample. The stratified estimator and variance are:

(5) $$\hat{\mu}_{ST} = \sum_{i=1}^{i} \frac{A_i}{A} \hat{\mu},$$

(6) $$\hat{\text{var}}(\hat{\mu}_{ST}) = \sum_{i=1}^{i} \left(\frac{A_i}{A} \right)^2 \hat{\text{var}}(\hat{\mu}_i)$$

where A_i is the area of each stratum, A is the total area, and $\hat{\mu}_i$ is the estimate for each stratum.

Finally, the adaptive stations were included under both the simple and stratified designs. The combined area was analyzed as if the top 5 stations were sampled adaptively, with the criterion value being the sixth highest of 496 kg/km. The total number of random stations was 42, with 51 additional adaptive stations. The random combined samples are also examined at the v' level.

Spatial analysis

Because the Hansen-Hurwitz estimator replaces each CPUE from initial random stations with its network mean, bias was tested for by examining within network spatial structure. A nonparametric Wilcoxon rank H-test (Freund and Walpole 1987) was performed to test for differences between bathymetry-parallel and bathymetry-perpendicular trawls in each cluster, as well as in the pooled data. The samples for each direction included the initial random station and all the samples extending on the same plane in the cluster. Since the slope and SR/RE strata were sampled linearly, they were not tested.

Analyzing spatial structure is often done with correlograms or variograms. Variograms are a generalized version of correlograms and are defined when correlograms are not (Cressie 1990). The purpose of constructing variograms is to show how population samples vary as a function of their distance apart. Variograms were constructed as defined in Cressie and Hawkins (1980) as follows:

(7)
$$2\bar{y}(h) = \left\{ \frac{1}{N(h)} \sum_{N(h)} \left| Z(s_i) - Z(s_j) \right|^{0.5} \right\}^4 \bigg/ \left(0.457 + 0.494 / \left| N(h) \right| \right)$$

where $|N(h)|$ is the number of distinct pairs of points $[Z(s_i), Z(s_j)]$, which are the CPUE values that are lagged by the distance h (in km). The denominator is a correction for bias. The result of the calculation is a set of pairwise variances at increasing distance from each other. This method was chosen because it is robust to contamination by outliers and because some of the top POP catches cause anomalous variogram behavior that can be resolved by the robust estimator. The point estimates were taken from the latitude and longitude of the halfway point of each tow and converted to kilometers apart with a Mercator conversion. The variograms were constrained for maximum distances to isolate structured variance and all bin sizes were held below twenty to smooth out the data. The fitted lines are variable span smoothers as defined by Friedman (1984). The general shape of the variogram is described by the nugget, range and sill. The nugget is the point where the variogram is extrapolated to the y-intercept and represents the unstructured variance (variance not described by spatial scale). The sill is the point where the variogram stabilizes (variance becomes unrelated to lag distance), which signifies the extent of the structured variance (the variance described by spatial scale). The range is the lag distance between the origin and the sill. I expect the range to be the distance from the initial station that ACS will add additional variability to the networks. Variograms were constructed for two simulated populations (Figure 3) to determine a standard of comparison. The clustered population exhibits mainly structured variance, while the unclustered population shows mainly unstructured variance. These variograms were compared with variograms constructed with historical triennial survey data, and variograms constructed with the data in this thesis.

The relationship between CPUE and depth was analyzed qualitatively for both POP and SR/RE in order to determine whether the sampling covered the likely range of these species.

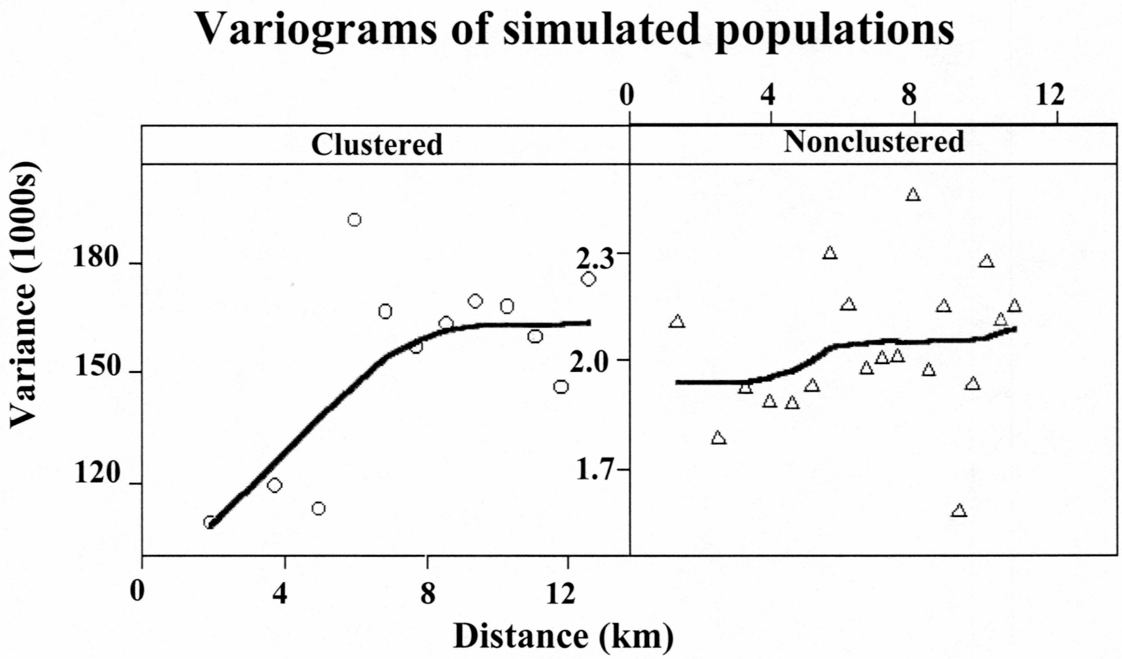

Figure 3. Variograms computed for catches from two simulated populations, one clustered, one unclustered, using the robust estimator from Cressie and Hawkins (1980) for pairwise variance compared to distance.

Diel movement analysis

A day versus night comparison for POP was made to determine if diel changes in catch rates might affect adaptive sampling. The time-of-day data were standardized to values between zero and one over a range of 24 hours beginning at 10 PM. Because the data were difficult to model, a categorical approach with four equal time intervals was also constructed. A Kruskal-Wallis rank test (Freund and Waldpole 1987) was used to compare survey catches among the four categories.

Results

Adaptive Sampling

One hundred ninety hauls were completed during the cruise. Of these, four were test tows, 81 were random stations, 103 were adaptive stations and two were invalid (one from major net hang-up and the other from wrong tow location). Implementation of the ACS design was straightforward. The random determination of tow direction was abandoned because of the small strata; all tows in each stratum were in the same direction. Nearly all the random and adaptive stations were trawled successfully; no station was omitted because of untrawlable bottom. However, net hang-ups or damage sometimes occurred, especially in the steep topography of the shortraker-rougheye study area.

The number of possible sampling units was determined *a posteriori*. This was accomplished by approximating the area of suitable habitat for each stratum. We then calculated the effective width of the trawl from a combination of the captain's estimates from his net sonar and the SCANMAR equipment (Appendix II) used on some of the hauls. The area was then divided by the mean trawl length (1.65 km) and by the mean trawl width (0.0021 km) yielding the possible number of samples for that stratum. The areas and possible samples are summarized in Table 2.

The predominant species caught during the cruise was POP. Total catches in individual hauls ranged up to 38 mt. For further details about the cruise and aspects of data collection and editing see Appendix II and for the summarized data by haul see Appendix III.

Summary information about the random and adaptive stations in each stratum is given in Table 2. One hundred forty-five stations were fished in POP strata and 36 fished in SR/RE strata. Of these, 89 POP tows and 12 SR/RE tows were conducted in the adaptive phase. After sampling in the slope and slope-gully intersection strata was completed, time constraints caused us to reduce the sampling in the remaining strata. Specifically, the number of random stations around which adaptive sampling occurred (r) had to be lowered from three in the slope and slope-gully intersection strata to only one or two in the remaining strata. The greatest sampling effort was in the slope-gully intersection stratum, where 51 total adaptive stations were fished because large concentrations of POP were encountered in that area. Thirty-six stations sampled during the adaptive phase were edge units. The standard adaptive estimators do not use these,

Table 2. Summary information on stations fished in each stratum during the 1998 adaptive sampling experiment for rockfish.

Stratum Network	A_i	N_i	n	r	$y>c$	v	v'	Network Units	Edge Units
				POP Study Area					
Intersection[1]	346	9800	15	3	245	66	59	44	8
Adaptive network 1								17	1
Adaptive network 2								14	3
Adaptive network 3								13	4
West gully	607	17200	15	2	214	26	16	1	10
Adaptive network 1								1	6
Adaptive network 2								0	4
East gully	648	18400	12	1	496	24	18	6	6
Adaptive network 1									6
Slope	596	16900	15	3	235	29	23	8	6
Adaptive network 1								3	2
Adaptive network 2								2	2
Adaptive network 3								3	2
Total	2917	62300	57			135	116	59	30
				SR/RE Study Area					
North	180	5100	12	2	1146	19	17	5	2
Adaptive network 1								3	1
Adaptive network 2								2	1
South	270	7700	12	2	479	17	13	1	4
Adaptive network 1								0	2
Adaptive network 2								1	2
Total	450	12800	24			36	30	6	6

[1]One of the initial random stations was also an edge unit. The three clusters merged to form a single network.

Notation

A_i= area of stratum (km^2)

N_i= number of possible samples

n = number of initial random stations.

r = number of high-CPUE stations around which adaptive sampling occurred.

$y > c$ = the criterion CPUE value (kg/km) used to determine whether adaptive sampling continued beyond the first level.

v = total number of stations fished (random + adaptive).

v' = number of stations used in the computation of the adaptive estimators (random + adaptive – edge units).

network units = number of stations in network with CPUE > criterion (excluding initial random stations meeting the criterion).

edge units = number of adaptive stations in network with CPUE < criterion (including those that were also initial random stations).

but the edge units can be utilized using the Rao-Blackwell Theorem (see Appendix IV). Criterion values of CPUE (*c*), for determining whether additional adaptive sampling would take place around adaptive hauls, ranged from 214 kg/km in the west gully stratum to 1,146 kg/km in the shortraker-rougheye north stratum.

Statistical results of the experiment by stratum are summarized for simple random sampling and the Hansen-Hurwitz and Horvitz-Thompson adaptive estimators (Table 3). The most notable differences occurred in the intersection stratum for POP and the north stratum for SR/RE. In general, the ACS results indicate a similar or decreased standard error for POP and an increased standard error for SR/RE when compared to the initial sample size for SRS. When using the increased sample size (v') in the SRS variance estimates, the ACS standard error was substantially lower than SRS only for the HT estimator in the Intersection stratum. In the remainder of the results using v', the SRS estimates and ACS estimates shared similar precision. The increase in estimated variance due to within-haul variation was negligible compared to between-haul variation (see Appendix I for further explanation of within-haul variance and a predictive model). A detailed presentation of the results for each stratum follows.

Table 3. Rockfish density estimates (kg/km) and associated statistics for each stratum in the adaptive sampling experiment conducted during F/V Unimak cruise 98-01. Results from three methods of estimation are shown: SRS using *n* (number of initial stations) and *v*' (equivalent number of samples used in adaptive estimates), the Hansen-Hurwitz adaptive estimator, and the Horvitz-Thompson adaptive estimator. Data are for Pacific ocean perch (POP) only in the POP study area, and for combined shortraker and rougheye rockfish in the SR/RE study area.

Stratum	Statistic	SRS (*n*)	SRS (*v*')	Hansen-Hurwitz	Horvitz-Thompson
POP study area					
Intersection					
	sample size	15	59	59	59
	abundance	789		600	251
	SE	444	224	276	173
	CV	56.3%	28.3%	46.0%	68.8%
West gully					
	sample size	15	16	16	16
	abundance	160		157	157
	SE	72	70	69	69
	CV	44.8%	43.4%	43.8%	43.7%
East gully					
	sample size	12	18	18	18
	abundance	191		185	185
	SE	115	94	109	109
	CV	60.1%	49.2%	59.0%	58.9%
Slope					
	sample size	15	23	23	23
	abundance	228		227	227
	SE	90	72	80	80
	CV	39.4%	31.8%	35.5%	35.4%
SR/RE study area					
North					
	sample size	12	17	17	17
	abundance	743		1,017	1,018
	SE	158	133	320	320
	CV	21.3%	17.9%	31.4%	31.4%
South					
	sample size	12	13	13	13
	abundance	279		279	279
	SE	69	66	70	70
	CV	24.9%	23.8%	24.9%	24.9%

Intersection

Fifteen random stations were fished; the top three were chosen for adaptive sampling. The criterion value, equal to the fourth highest CPUE of POP in the random tows, was 251 kg/km. The adaptive sampling design was conducted in a cross pattern and resulted in the sampling patterns shown in Figures 4-6 (pp.24-25). The amount of adaptive sampling was extensive, with 44 stations exceeding the criterion value. The stopping rule was enacted on all three of the networks. Eight stations were edge units and not used in the estimates.

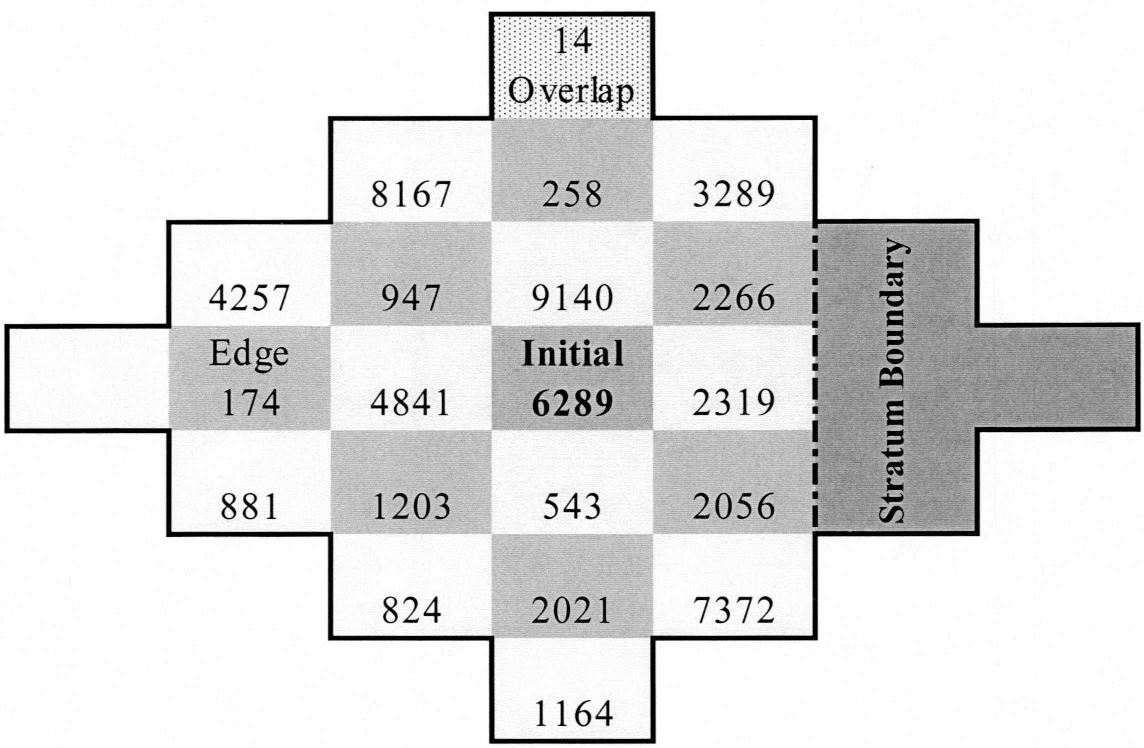

Figure 4. Intersection station 15 adaptive pattern.

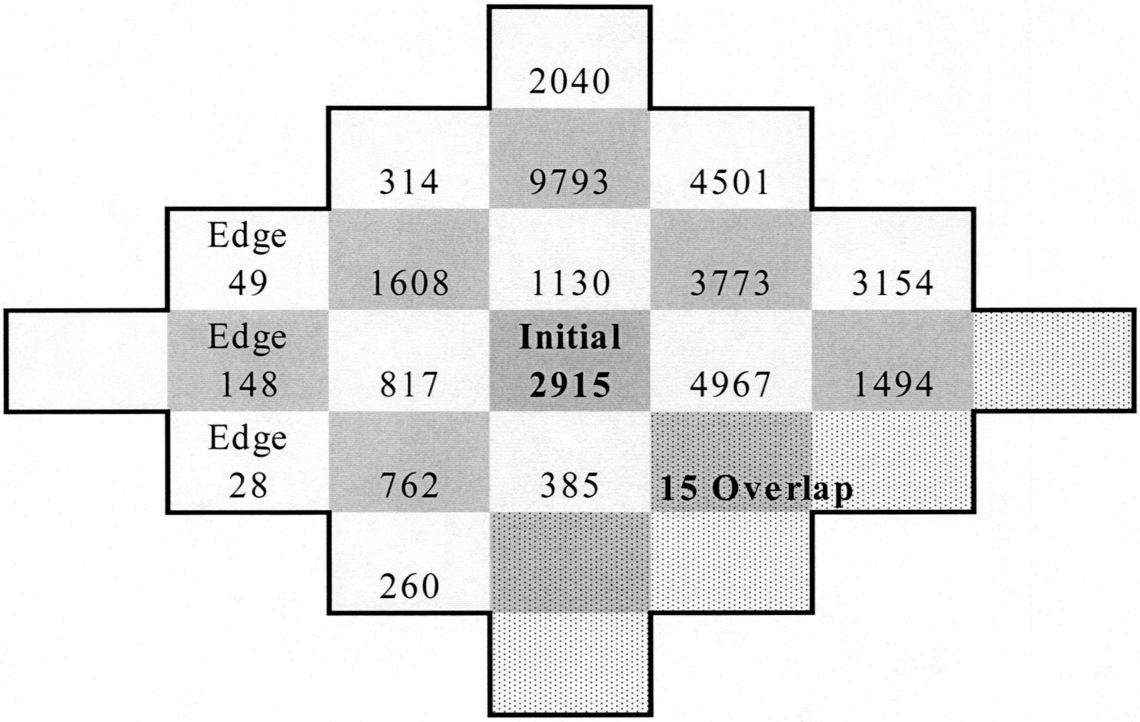

Figure 5. Intersection station 14 adaptive pattern.

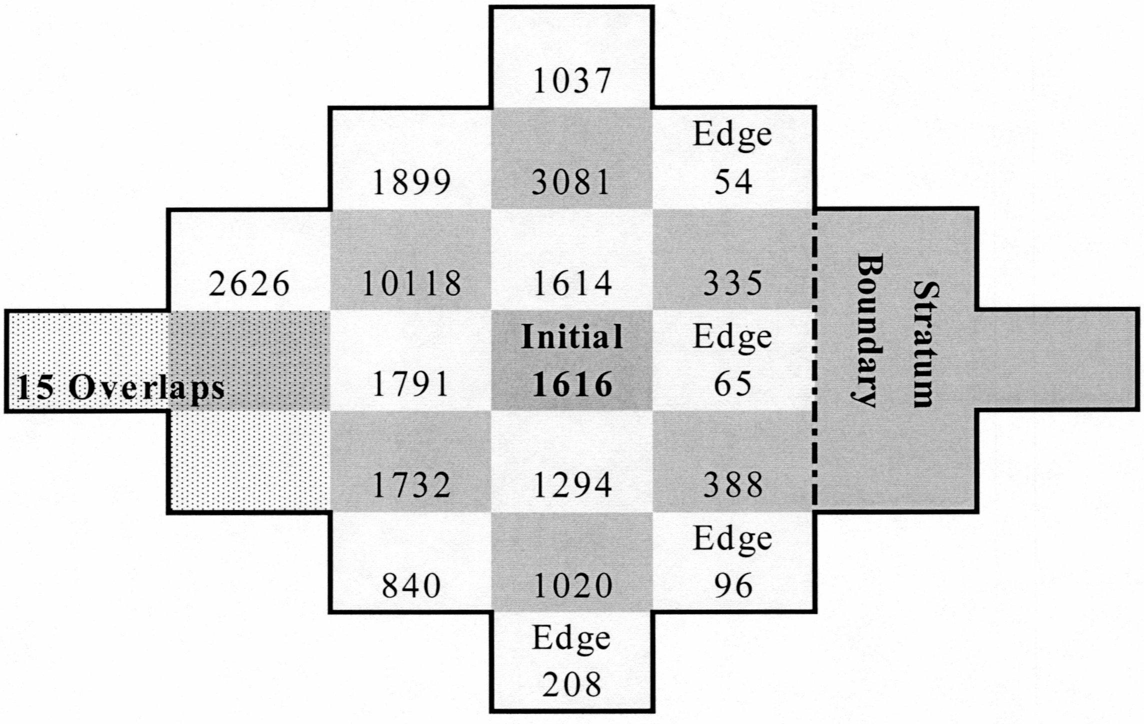

Figure 6. Intersection station 9 adaptive pattern.

Because of the extensive sampling in a small area, all three adaptive sampling clusters overlapped to form one large network (Figure 7). This overlap of clusters caused substantially different abundance estimates (Table 3, p.23) between the two adaptive estimators, i.e., 600 kg/km for Hansen-Hurwitz vs. 252 kg/km for Horvitz-Thompson, because the HH estimator makes repeated use of this network for the three SRS units, while the HT estimator uses only distinct networks. All three abundance estimates were at least 30% different from each other. The Hansen-Hurwitz estimator had a substantially lower CV than SRS, whereas CV of the Horvitz-Thompson estimator was much higher. However, the Horvitz-Thompson estimator had the lowest SE. The SRS method had the highest SE, but also the highest abundance estimate. However, if the additional effort of sampling (v') in the adaptive phase had been used in simple random sampling, the latter's SE and CV would have been halved, yielding values comparable to or lower than those for ACS (Table 3, p.23).

To examine the sensitivity of the HT estimator, the data were analyzed with the supernetwork treated as three different networks (which is theoretically inappropriate). The HT mean estimate was 595 kg/km (SE 322), which was more similar to the HH estimate. Additionally, a stopping rule of one was applied to the three networks to see what would happen if the networks were not allowed to overlap. This led to a surprisingly (because 35 samples were removed) good result of 617 kg/km (SE 333) for the HH mean estimate and 619 kg/km (SE 334) for the HT estimate.

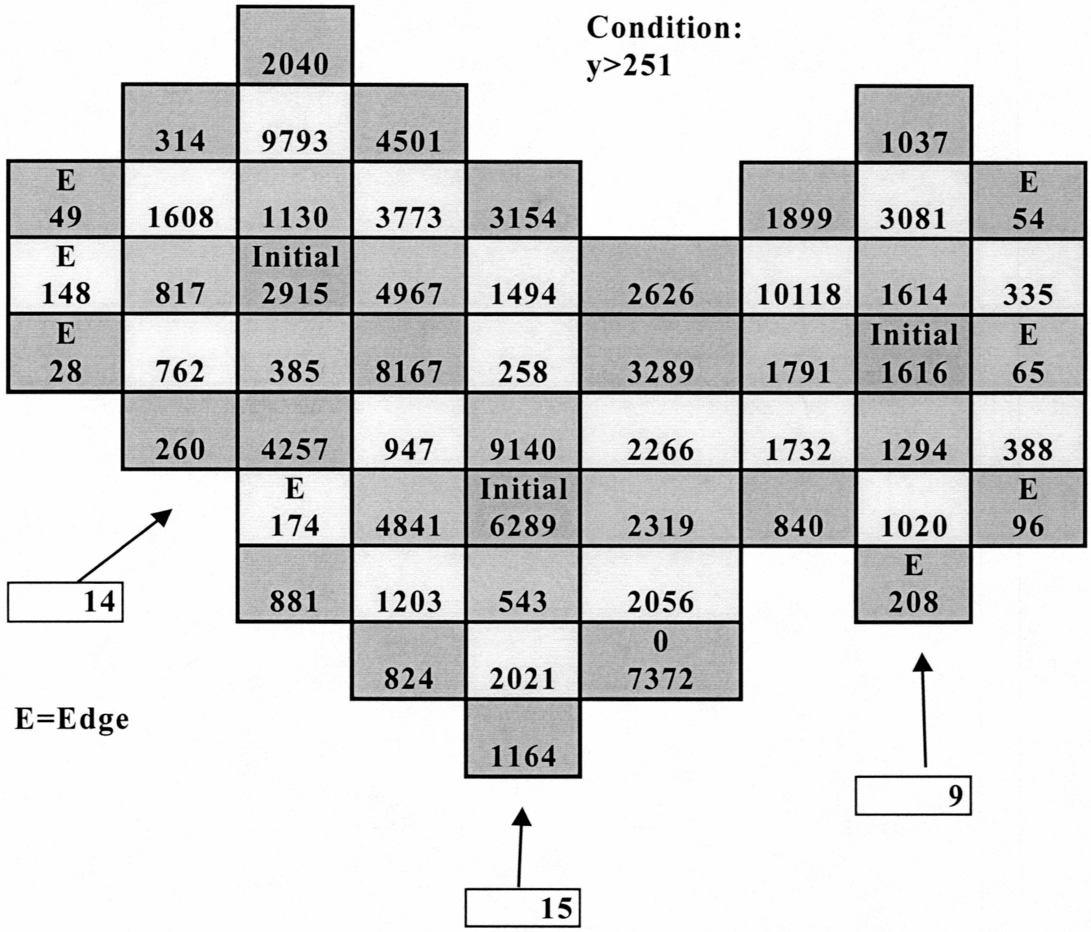

Figure 7. Adaptive "supernetwork" resulting from overlap of three close networks in the intersection stratum for Pacific ocean perch. Numbers represent CPUE values, "Initial" is the initial random station and E denotes edge unit.

Example

The following is an overview of how the calculations were done for the intersection stratum. This stratum is illustrated here because it is the most complicated of the strata presented in the thesis. The three stations with the highest CPUEs were adaptively sampled, with all three networks eventually overlapping.

The initial random sample size was n =15. A total of N=9800 was approximated by taking the total area of 346 km^2 and dividing by the average area swept and rounding to two significant figures as follows,

$$N = \frac{A_i}{\bar{l} \times \overline{w}} = \frac{346\text{km}^2}{1.65\text{km} \times 0.021\text{km}} = 9809 \sim 9800,$$

where $\bar{l}$ is the average trawl length and $\overline{w}$ is the average width of the net.

The initial y_i values in rank order were:

6289 **2915** **1616** 251 179 168 105 68 58 54 45 29 28 15 15

The top three networks were adaptively sampled resulting in three overlapping networks:

6289	8168	258	3290	4258	947	9141	2266	4841	2319	881	1203	543	2056	825	2021	7373	1165
2915	2041	314	9794	4502	1609	1131	3773	3154	818	4967	1494	762	385	260			
1616	1037	1899	3081	2627	10119	1614	335	1791	1732	1294	388	840	1020				

SRS Estimates

The simple random sampling mean estimate and its estimated variance are

$$\hat{\mu}_{SRS} = \frac{1}{n}\sum_{i=1}^{n} y_i = 789 \text{ and}$$

$$\hat{\text{var}}(\hat{\mu}_{SRS}) = \left(1 - \frac{n}{N}\right)\frac{\sum_{i=1}^{n}(y_i - \hat{\mu}_{SRS})^2}{n_1} = 197{,}448.$$

Hansen-Hurwitz estimates

The values in the top three networks are averaged. In this case, all three networks overlapped so the average of all three networks is used for the first three w_i values.

$w_{1\text{-}3}$=2,663

$w_{4\text{-}15}$=	251	179	168	105	68	58	54	45	29	28	15	15

which are the remaining initial sample values that did not exceed the criterion.

Proceeding as if the w_i values were taken as a simple random sample,

$$\hat{\mu}_{HH} = \frac{1}{n_1}\sum_{i=1}^{n} w_i = 600 \text{ and}$$

$$\tilde{\text{var}}(\hat{\mu}_{HH}) = \left(1 - \frac{n_1}{N}\right)\frac{\sum_{i=1}^{n}(w_i - \hat{\mu}_{HH})^2}{n_1} = 76{,}256\,.$$

Horvitz-Thompson estimates

Since the Horvitz-Thompson estimator relies solely on distinct networks, the three overlapping networks are treated as one large network. The total, y_k^*, and the intersection probability, α_k, of each network k are necessary to calculate the mean.

The resultant calculations are:

$$\alpha_k = 1 - \binom{N - x_k}{n} \Big/ \binom{N}{n}$$

$$\alpha_1 = 1 - \binom{9800 - 47}{15} \Big/ \binom{9800}{15} = 0.070$$

Probability of intersecting the combined 3 networks (47 stations)

$$\alpha_{2-13} = 1 - \binom{9800 - 1}{15} \Big/ \binom{9800}{15} = 0.0015$$

Probability of intersecting the remaining 12 networks (size 1)

$$y_1^* = 47 * 2{,}663 = 125{,}151$$

Network size times the network mean

$$y_{2-13}^* = y_{4-15}$$

Because the first three networks are merged 1, 4-15 becomes 2-13.

The estimate of mean density is then

$$\hat{\mu}_{HT} = \frac{1}{N} \sum_{k=1}^{\kappa} \frac{y_k^*}{\alpha_k} = 251.$$

Calculating the variance for the HT estimator is slightly more complex than the HH estimator as joint intersection probabilities, α_{jk} need to be calculated:

$$\alpha_{jk} = 1 - \left[\binom{N - x_j}{n_1} + \binom{N - x_k}{n_1} - \binom{N - x_k - x_k}{n_1} \right] \Big/ \binom{N}{n_1}$$

All of the joint intersection probabilities with network 1 of 47 units and networks 2-13 of 1 unit are equal:

$$\alpha_{1,2-13} = 1 - \left[\binom{9800 - 47}{15} + \binom{9800 - 1}{15} - \binom{9800 - 47 - 1}{15} \right] \Big/ \binom{9800}{15} = 0.0000997$$

All of the remaining joint intersection probabilities are combinations of networks 2-13 of size 1:

$$\alpha_{2,3-13} = 1 - \left[\binom{9800 - 1}{15} + \binom{9800 - 1}{15} - \binom{9800 - 1 - 1}{15} \right] \Big/ \binom{9800}{15} = 0.00000219$$

leading to an estimated variance of

$$\hat{\text{var}}(\hat{\mu}_{HT}) = \frac{1}{N^2}\left[\sum_{1}^{\kappa}\sum_{1}^{\kappa}\frac{y_j^* y_k^*}{\alpha_{jk}}\left(\frac{\alpha_{jk}}{\alpha_j \alpha_k} - 1\right)\right] = 30{,}003$$

A final example calculation is to treat the simple random variance as if the same number of samples were used as in the adaptive estimators (ν'=59). The reason for doing this is to make the theoretical comparison fairer in that we are comparing the same number of samples in each estimator. This reduces the SEs and CVs substantially (Table 3, p.23). The resultant variance calculation is:

$$\hat{\text{var}}^*(\hat{\mu}_{SRS}) = \left(1 - \frac{\nu'}{N}\right)\frac{\sum_{i=1}^{n}(y_i - \hat{\mu}_{SRS})^2}{\nu'} = 49{,}953\,.$$

West Gully

Fifteen random stations were fished; the top two stations were chosen for adaptive sampling. The criterion value, equal to the third highest CPUE of POP in the random tows, was 214 kg/km. The adaptive sampling design was conducted in the cross sampling patterns shown in Figures 8-9. Adaptive effort was low, with only one station exceeding the criterion value. The stopping rule was not invoked in this stratum. Ten stations were edge units and not used in the estimates. The differences between the three estimators (Table 3, p.23) were slight, and CVs were similar. SRS using *v*' yielded similar results.

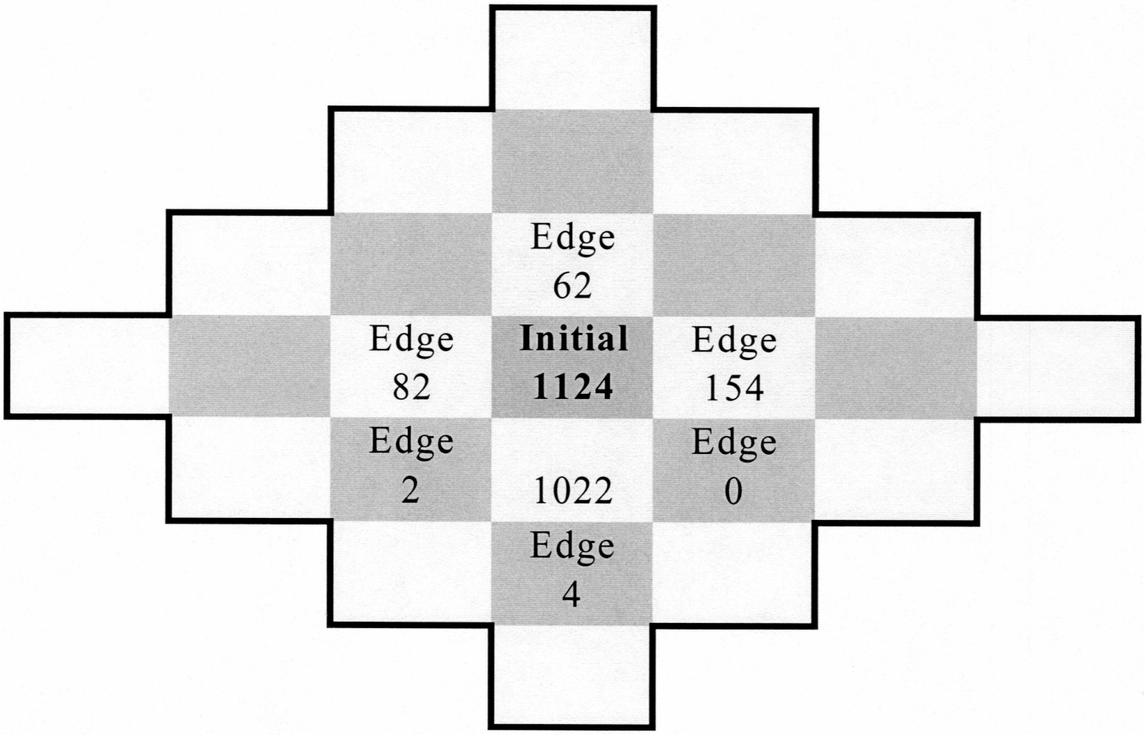

Figure 8. West gully station 37 adaptive pattern.

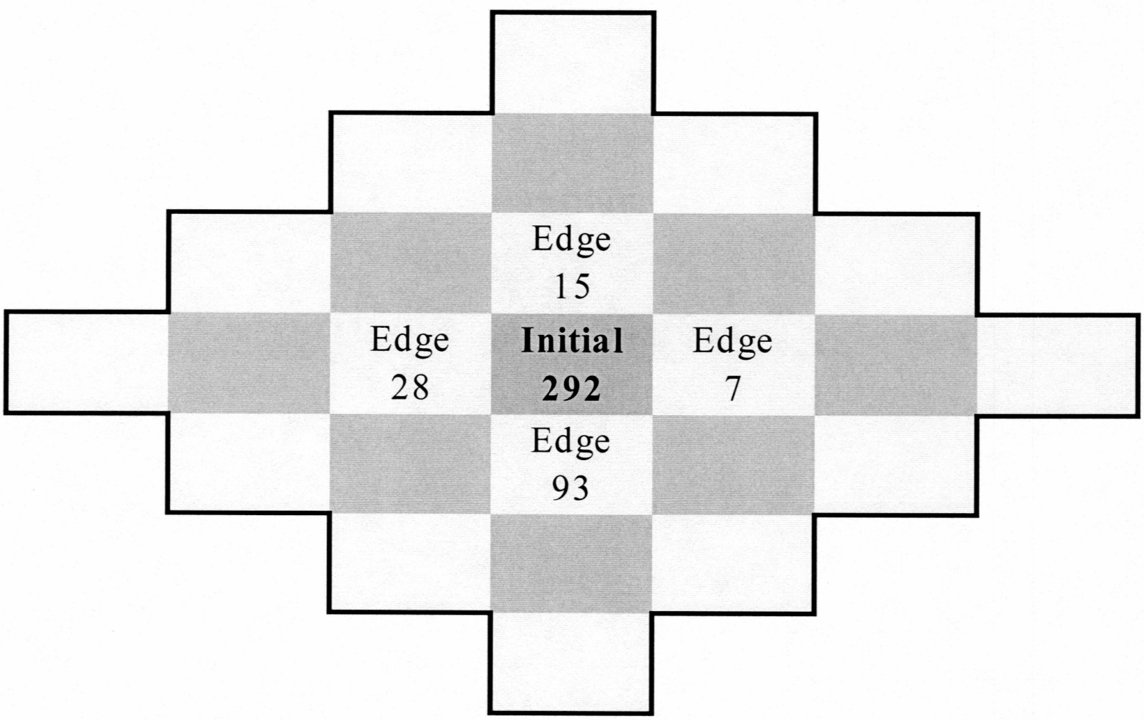

Figure 9. West gully station 35 adaptive pattern.

East Gully

Twelve random stations were fished; the top station was chosen for adaptive sampling. The criterion value, equal to the second highest CPUE of POP in the random tows, was 496 kg/km. Adaptive sampling was conducted in a cross pattern (Figure 10), and adaptive effort was moderate, with five stations exceeding the criterion value. The stopping rule curtailed sampling along the lower end of the network in Figure 10. Six of the sampled stations were edge units and not used in the estimates. The three different abundance estimates (Table 3, p.23) were similar, as were their CVs. SRS using *v*' yielded a slightly lower SE and CV than ACS.

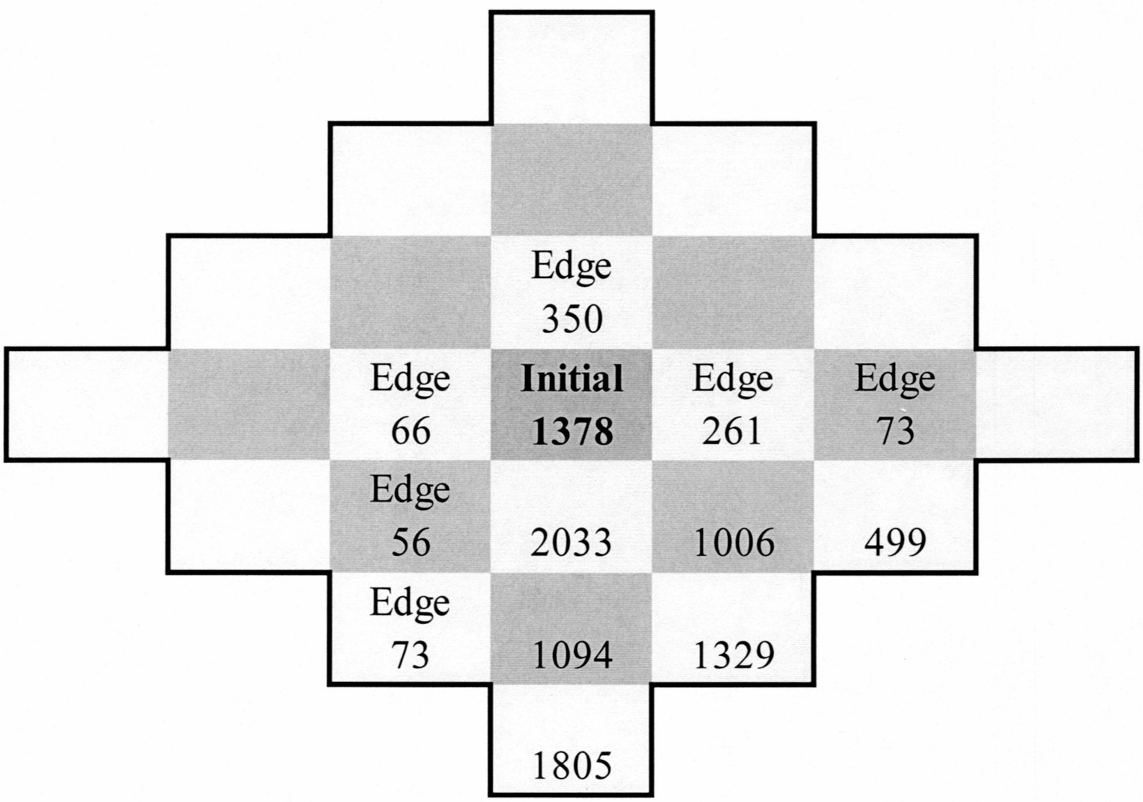

Figure 10. East gully station 56 adaptive pattern.

Slope

Fifteen random stations were fished; the top three stations were chosen for adaptive sampling. The criterion value, equal to the fourth highest CPUE of POP in the random tows, was 235 kg/km. The amount of adaptive sampling, which was in a linear pattern (Figure 11), was moderate, with eight stations exceeding the criterion value. The stopping rule was not invoked in this stratum. Six stations were edge units. The three abundance estimates (Table 3, p.23) were similar here, with a slight decrease (4%) in CV for the adaptive estimators. SRS using *v'* gave a lower SE and CV than ACS.

Edge			**Initial**		Edge	
218	2423	416	**897**	293	139	

	Edge		**Initial**		Edge	
	227	651	**303**	761	123	

	Edge		**Initial**			Edge
	138	996	**1196**	284	721	229

Figure 11. Slope stations 84, 91, 90 adaptive patterns.

Shortraker-Rougheye North

Twelve random stations were fished; the top two were chosen for adaptive sampling. The criterion value, equivalent to the third highest SR/RE CPUE, was 1,146 kg/km. Adaptive sampling was conducted in a linear pattern (Figure 12), and adaptive effort was moderate, with five stations exceeding the criterion value. The stopping rule was not invoked in this stratum. There was no network overlap, but each network was truncated by the southern stratum boundary. Two of the stations were edge units. The abundance estimates (Table 3, p.23) were ~37% higher for both adaptive estimates, with an increase in CV of ~10% for each as compared with SRS. SRS using *v*' yielded a more substantial decrease in SE and CV compared to ACS. Most of the adaptive stations had higher CPUEs than those in the initial random stations. These higher densities may not have been discovered in simple random sampling, even with much greater effort.

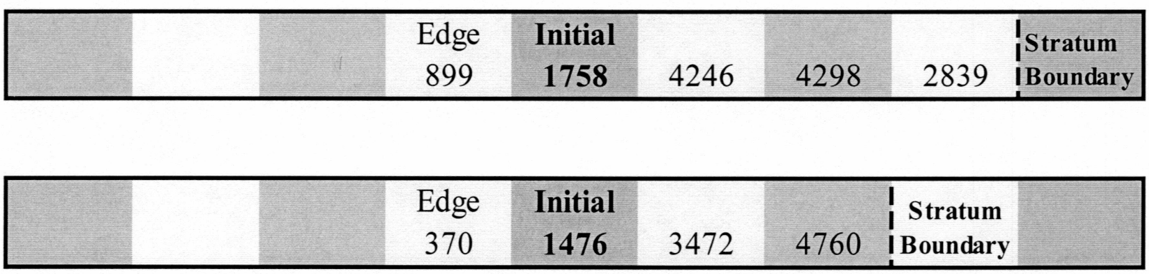

Figure 12. Shortraker/Rougheye north stations 118,113 adaptive patterns.

Shortraker-Rougheye South

Twelve random stations were fished; the top two were chosen for adaptive sampling. The criterion value, equal to the third highest SR/RE CPUE, was 479 kg/km. Adaptive sampling was conducted in a linear pattern (Figure 13), and adaptive effort was low, with only one station exceeding the criterion value. The stopping rule was not invoked in this stratum. Four stations were edge units. The three different abundance estimates and their associated SEs and CVs were nearly identical.

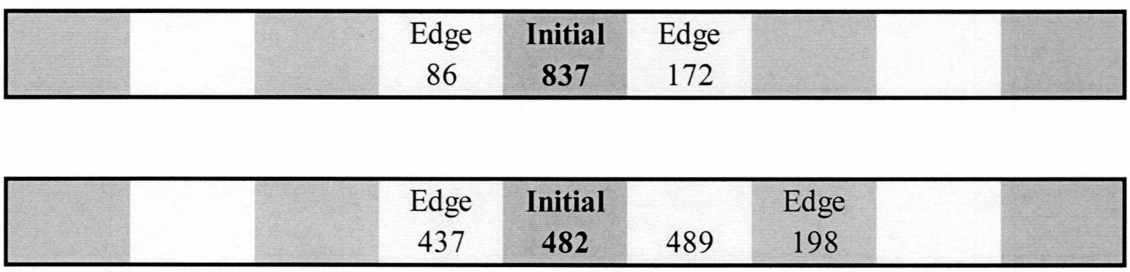

Figure 13. Shortraker/Rougheye south stations 109, 119 adaptive patterns.

Stratification

The intersection and gully areas were combined to produce an overall density estimate using their areas (Table 2, p.21) to weight each stratum. Stratification and ACS had a similar and synergistic effect on the precision of the estimation results (Table 4). The unstratified SRS estimator has the highest SE, while the unstratified adaptive estimators and the area-weighted stratified estimator show similar reductions in SE. The stratified adaptive sampling estimators showed the largest reduction in SE. The same qualitative results occur with CV except the magnitude of effect is smaller. If the larger sampling size (v') is used, the SE for stratified random sampling (66) is only slightly higher than the SE for the stratified adaptive HT estimate (64), which was the lowest of all estimates. A surprising result is the reduction in the point estimate with increasing stratification and/or adaptive sampling. Theoretically, all estimates should be similar (although adaptive estimators may have some small bias), and the large SEs for the estimates do indicate that the differences are not statistically significant. Stratification produced a lower estimate because the intersection stratum has the largest mean estimate, but the smallest area, so it does not affect the overall mean as much as when the data are pooled across the whole area. Combining all strata into one adaptive sample also reduces the mean estimate, because the adaptive networks in five of seven cases tend to average down the initial random sample. Thus, in this case both stratification and adaptive sampling act to reduce the effect of a large catch on the overall estimation in this case.

Table 4. Comparison of stratified sampling versus whole area estimates of Pacific ocean perch (POP) mean density for the combined intersection and gully areas. The stratified estimates are weighted by area. Since the slope area was adaptively sampled linearly, it is not included SRS values are calculated with n=42. Parenthetical values are SRS estimates calculated with v'=93.

Whole area SRS μ=394 SE=167 (*115*) CV=42% (*29%*)	
Stratified SRS μ=308 SE=110 (*66*) CV=36% (*22%*)	**Whole area adaptive** μ(HH)=341 μ(HT)=277 SE=120 SE=105 CV=35% CV=38%
Stratified Adaptive μ(HH)=264 μ(HT)=188 SE=79 SE=64 CV=30% CV=34%	

Spatial Results

Wilcoxon Rank H-tests show no significant difference between the bathymetry-parallel means of the clusters versus the bathymetry-perpendicular means of the clusters both in individual clusters and in the pooled data ($p>0.10$). This result suggests that there is no detectable bias in the Hansen-Hurwitz estimator with a stopping rule due to within-network spatial structure. A caveat to this suggestion is that there may be some differences in CPUE for stations within a network beyond the area delimited by the stopping rule.

Variogram analysis on each stratum had mixed results (Figure 14). In the SR/RE strata, it can be seen that the variability is not structured with distance. The north stratum has a large nugget of the order of $\sim 10^6$ (where the curve intercepts the y-axis), and little evidence of any sill. The south stratum has a much smaller nugget ($\sim 10^4$), and no apparent sill, representing unstructured variance. Unlike the SR/RE strata, the POP surveys were conducted over several different habitat types. In the two gully areas and the slope strata, there is very little structured variance present. The east gully stratum has a possible but not prominent sill at 2 km. The west gully shows no structured variance. The intersection, however, shows some structure in the variance. While the unstructured variance is still large, the variogram shows increasing structured variance out to a sill at ~3.8km. Variograms constructed for the combined strata showed more structure in the variance (Figure 15, p.40). This supports the idea that overstratification may have occurred as the larger area exhibits the expected type of structure for POP, while

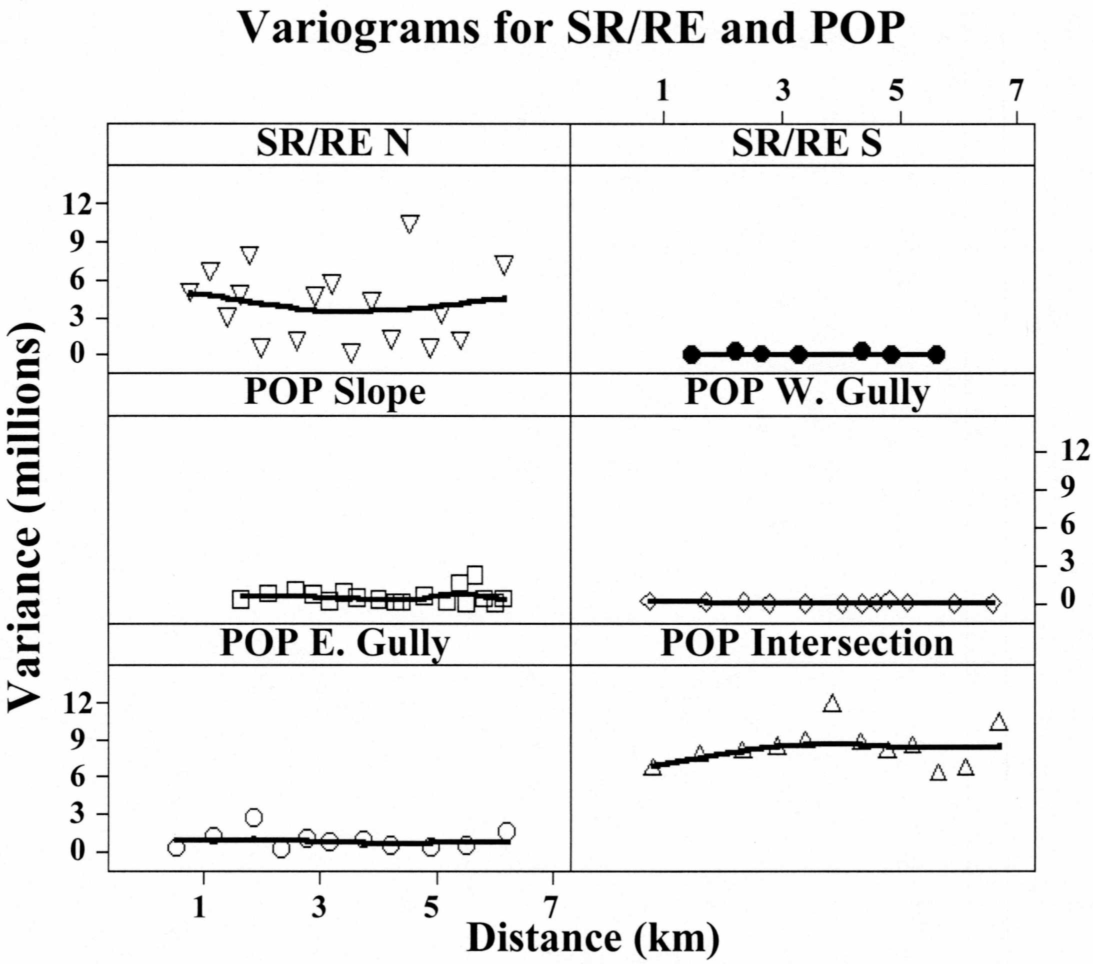

Figure 14. Variograms of individual strata from the Unimak 98-01 sampling cruise computed with the robust estimator from Cressie and Hawkins (1980) for pairwise variance compared to distance.

SR/RE still shows little structure. Variograms of POP and SR rockfish catches for the entire Gulf of Alaska, taken from the combined data from the 1990, 1993, and 1996 NMFS triennial surveys show similar trends (Figure 16). The SR variogram shows no structured variance while the POP variogram shows an ideal variogram with primarily structured variance.

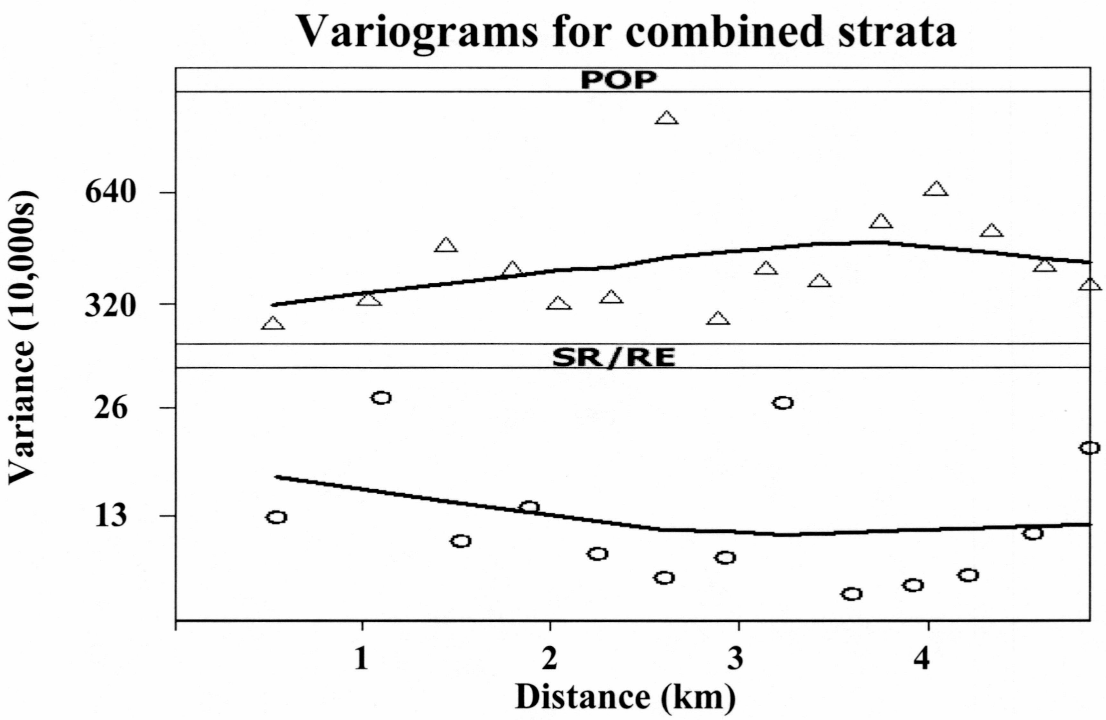

Figure 15. Variograms of combined strata from the Unimak 98-01 sampling cruise computed with the robust estimator from Cressie and Hawkins (1980) for pairwise variance compared to distance.

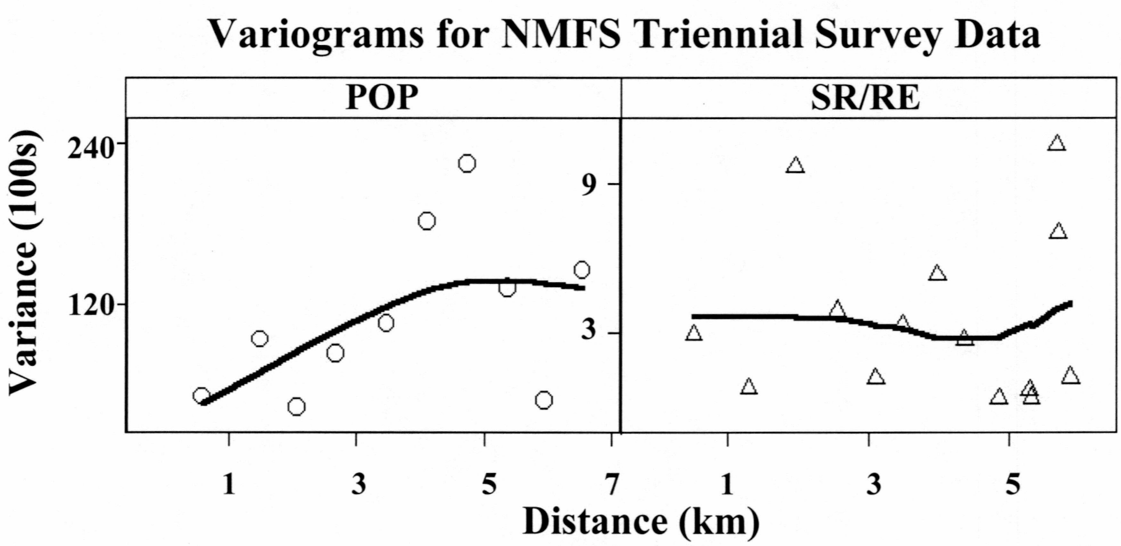

Figure 16. Variograms computed for NMFS triennial survey data for Pacific ocean perch (POP) and shortraker rockfish (SR) catches with robust estimator from Cressie and Hawkins (1980) for pairwise variance compared to distance.

The catches of both POP and SR/RE vary considerably with depth (Figure 17). POP catches are maximized at a depth of ~200 m, excluding an exceptional catch of ~25,000 kg/km at 304 m (not shown on figure, to keep a reasonable scale). Sizeable catches (>1500 kg) are almost exclusively found between 180 and 250 m, with only three exceptions in deeper depths. SR/RE catches are more dependent on depth than POP. SR/RE catches maximize at a depth of ~370 m (Figure 17). The eight largest catches are within in a tight range between 362 m and 384 m. The catch distribution drops off rapidly at depths less than 300 m and greater than 400 m.

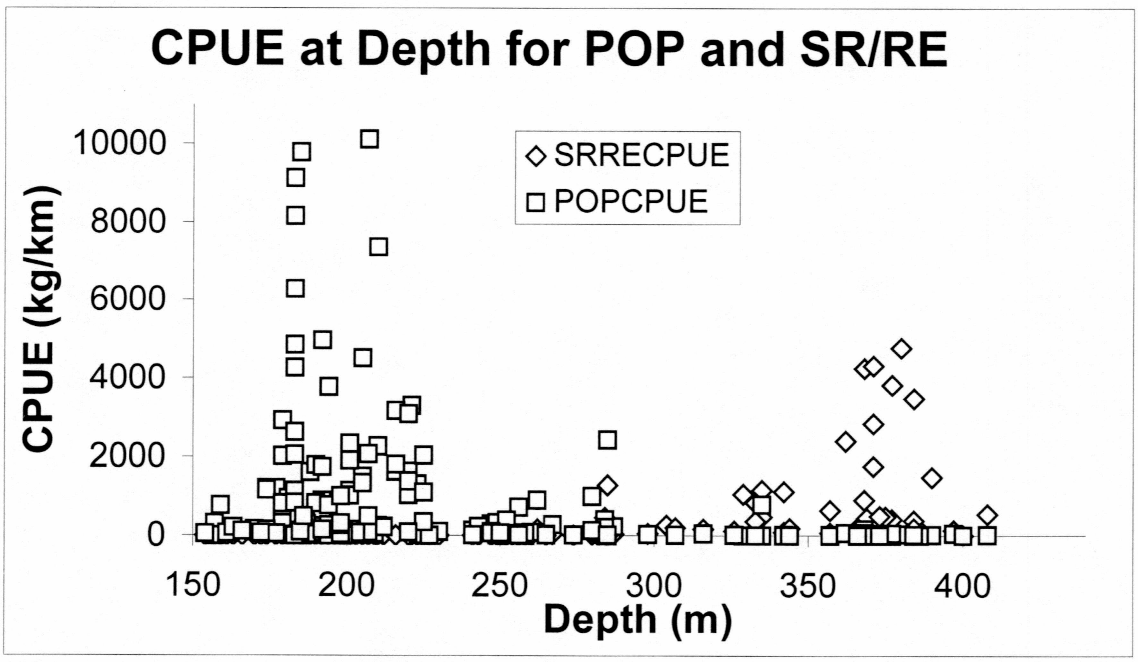

Figure 17. Catch per unit effort (CPUE) versus depth for Unimak 98-01 Pacific ocean perch (POP) and shortraker/rougheye (SR/RE) catches. No tows were made below 150 m depth or above 450 m depth. Triangles represent SR/RE and circles represent POP.

Diel Results

Consensus among commercial fishing captains is that day catches far exceed night catches. Diel vertical migrations of POP have been documented in the past (Balsiger et al. 1985). Changes in light and feeding behavior can cause POP to ascend to 40 m off bottom (Moiseev and Paraketsov 1961). In the data collected for this study, this migration is not easily discernable in the catches with a continuous model (Figure 18). The data were broken up into the four time intervals (Table 5) based on the daylight for the area and time of year.

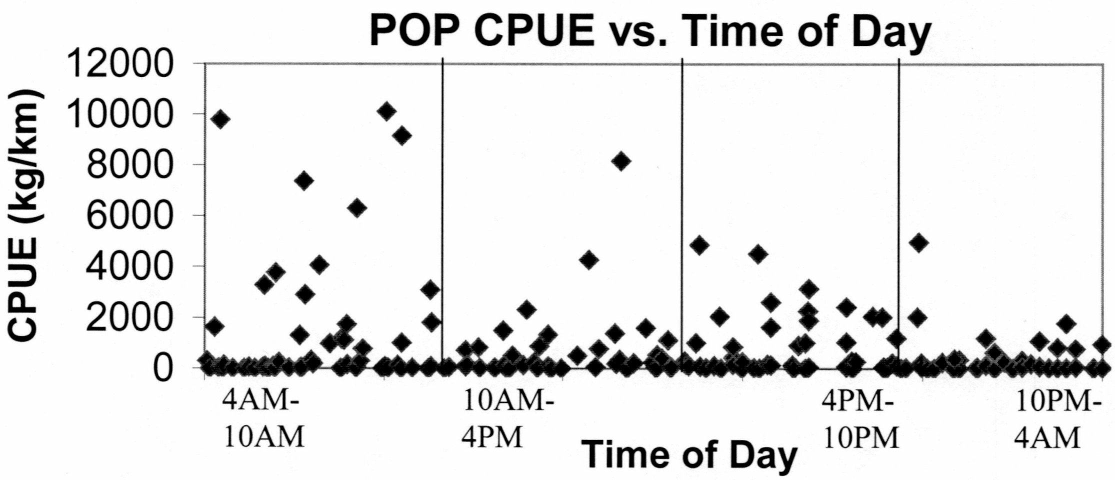

Figure 18. Unimak 98-01 Pacific ocean perch (POP) catch-per-unit effort (CPUE) versus time of day. CPUE axis constrained to 12,000 due to one large outlier (25,000 kg/km).

Table 5. Mean Pacific ocean perch (POP) catch-per-unit effort (CPUE) of four time categories throughout the day (excluding 25,000 kg/km outlier).

Time	Mean	SE
10 PM-4AM	358.2	110.9
4AM-10AM	1385.9	362.5
10AM-4PM	755.4	244.0
4PM-10AM	836.9	172.6

Upon inspection of the means for each time period, the smallest catches occurred during the period of complete darkness (10PM-4AM) and the largest occurred during the early morning (4AM-10AM). A nonparametric Kruskal-Wallis test did indicate that there are larger catches in the morning period ($p<0.04$) with more significant results when the 25,000 kg/km outlier was included. Additionally, most of the huge catches (>5000kg) were collected during the day. Bottom trawls may be missing a substantial portion of the population at night because it is in midwater. This effect may be amplified in commercial boats because often they only trawl when an exceptional potential catch is sighted on hydroacoustics and then process throughout the night. This should have little effect on the adaptive sampling procedure because the criterion will usually be much smaller than these exceptional catches, but may affect the estimates.

Discussion

This application of adaptive cluster sampling was straightforward, had no logistical difficulties and allowed the survey to be changed as the cruise progressed. Modest gains in survey precision were obtained for POP with adaptive sampling. When compared with simple random sampling using *n*, SE and CV for at least one adaptive estimator of POP abundance decreased in all four strata sampled. This improvement was most noticeable for the combined area.

In order to test the first hypothesis that adaptive sampling of POP is better than simple random sampling, some adjustment for sample size is needed. ACS, by definition, adds more samples to the initial random sample, which by design will lower the SE. Thompson and Seber (1996) use v (the total adaptive sample size, including edge units) to compare SRS with the adaptive estimators. For a fairer theoretical comparison, it is better to compare the standard errors of the estimators using the same number of samples used in the estimates (v', edge units are not used in the estimate). In this way, we predict the SE of simple random sampling if we had actually taken the same number of samples in a random fashion. When the SRS SEs are calculated using v', they are usually lower than the adaptive SEs (Table 3, p.23). In these cases, the precision of SRS is estimated to be higher than adaptive sampling if the additional effort in adaptive sampling had been applied to random sampling. Therefore, the hypothesis that ACS is better than SRS for these rockfish remains unresolved by the field results.

The POP study area was divided into four strata representing different habitat types in order to see how adaptive sampling worked with different densities and clusters of fish. However, such stratification increases the sampling efficiency of simple random sampling prior to adaptive sampling, because stratification usually improves estimation of mean density. Additionally, it may reduce the efficacy of adaptive sampling as indicated by the difference between the combined and stratified variograms (Figure 15, p.40). Adaptive sampling reduces the SE equivalently to that of stratification of the initial samples, but stratified random sampling using the v' sample size is more effective than ACS alone (Table 4, p.37). The combination of the two methods results in a lower

SE than ACS alone, suggesting that the adaptive sampling is accounting for small-scale variation within networks, while stratification is accounting for large-scale variation related to habitat. Additionally, adaptive sampling over a broader area improves the precision of the estimate. The comparison between the stratified and unstratified estimators shows us that adaptive sampling does take advantage of small-scale spatial structure, but astute stratification--if habitat knowledge is available--can lead to more significant gains than adaptive sampling alone. This could also mean that adaptive sampling would be appropriate when little is known about habitat structure prior to the survey. Therefore, future experimentation would need to account for the interaction of stratification and adaptive sampling.

The intersection stratum is where clusters of fish were encountered and adaptive sampling should have worked best. Indeed, the drops in abundance, SE and CV for the Hansen-Hurwitz estimator compared with those for simple random sampling (using n) were greatest here. The Horvitz-Thompson estimate and its SE were even lower, but its CV was higher because of the great reduction in estimated abundance. The differences between the HH and HT estimators are mainly due to the repeated use of the merged network (Figure 7, p.27) in the HH estimator for each initial unit intersecting this network; it is used only once in the HT estimator because the calculation uses only distinct networks. Discerning which estimator is better in this case is difficult, because the results from adaptive sampling were so variable and this result is one realization of a random process (many samples may have resulted in comparable estimates). All the same, the merging of networks occurred because the size of the intersection stratum was small. Further experimentation and research should investigate the effects of small areas versus large areas on adaptive sampling estimates.

Much of the adaptive sampling time was spent on the intersection stratum. This caused the effort put into the other strata to be reduced. In doing so, the order statistics required us to raise the criterion value to the second or third ranked station in the initial samples; this may have been too high of a criterion value for these particular areas, because mainly edge units resulted from the gully sampling. Consequently, not much insight is gained in these particular strata. Nevertheless, these areas were probably less interesting from the point of view of improving the triennial survey, because density of POP was apparently low.

Our second hypothesis was that adaptive sampling would be less beneficial in surveying abundance of SR/RE, because it is believed that they were not as clustered as POP. This hypothesis is supported by the fact that the SRS estimates for SR/RE are more precise than adaptive estimates, even using n in the SRS estimates. However, aggregations in the north stratum were found by adaptive sampling that were not found by simple random sampling, and consequently, adaptive sampling resulted in higher SE values and a considerable increase in abundance estimates compared with simple random sampling. The higher SEs for adaptive estimators in this instance may not be an indication of an inferior approach, but that the sampling happened to obtain higher CPUEs. Additional insight is gained into the population than would be with SRS alone. For the south stratum, results of random and adaptive sampling were almost identical and in accord with the null hypothesis. Therefore, examining this small trial would lend support to the hypothesis, but insufficient data were collected for any significant conclusions.

One ancillary factor that may also be important when evaluating adaptive sampling is whether it is more efficient than simple random sampling in terms of practicalities such as cost and time. Additional costs are incurred in adaptive sampling because stations are added. Of practical interest is how precise are adaptive sampling estimates compared with a conventional simple random sampling design for the same costs. The expected number of stations sampled and travel time between survey stations are important factors when considering costs (Thompson and Seber 1996), but this information was not collected in the 1998 survey. It is expected with adaptive sampling, there is less travel time and, therefore, lower costs per sampling station because sampling is within a network of nearby units. Adaptive sampling likely allowed much more time for trawling than if only simple random sampling had been conducted. For an equal amount of sampling time (as contrasted to equal sample size), the precision for SRS is bounded by the unadjusted and adjusted SE's, which overlap the adaptive SEs leaving cost and practicality as important issues in deciding which design is better. Factors that influence the merits of adaptive sampling as a practical survey design for slope rockfish will be the focus of analyses and field experiments in the future.

A definitive feature of the ACSORD design used in this study is that all initial random stations must be sampled before the adaptive phase. If adaptive sampling is to be applied to the triennial trawl survey in the Gulf of Alaska, this design may not be practical, because it could require too much travel time back to the high-density stations.

If information is available beforehand, the criterion can be determined before the random stations begin, saving travel time and preventing possible fish movement. Alternative adaptive cluster designs will be examined in future experiments, wherein the criterion for adaptive sampling is determined beforehand from existing data or from previously sampled strata.

The stopping rule was not invoked many times (5 of 13), but its necessity was evident in the intersection stratum. In an ACSORD design, the criterion value used can be relatively low in a high-density stratum. Without a stopping rule, this can make the completion of the adaptive sampling intractable. For the small bias induced (Su and Quinn *unpublished work*), the stopping rule can be useful. However, if a relatively high criterion is fixed ahead of time, the stopping rule may be eliminated.

Based on previous literature and the pilot study done on ACS for rockfish, different results were expected. There are several possibilities why the results were contrary to expectations. First, this was an area of known rockfish habitats and abundance, and the stratification was done using this information. When combined with other variance reducing sampling designs, ACS is not as effective. Second, the rockfish aggregations were not as strong as expected. High aggregation is critical to the efficiency of ACS. Third, the study area was small, which resulted in stratum boundaries being reached and networks overlapping.

The variogram analysis provides some support for the idea that adaptive cluster sampling is beneficial for POP and not for SR/RE. Since the idea behind ACS is to maximize within-network variability, ACS is more effective when there is a substantial portion of structured variance in the variogram. The intersection showed the most promise for this in the variograms, and indeed, it was the stratum that showed the most clustering. By inspecting the range to the sill in the intersection variogram, gains in precision can be expected from adaptive sampling within 3-4 km of the initial random station. If individual strata had produced variograms similar to the combined strata, previous NMFS data and the simulated population, greater gains might have been achieved. In the SR/RE areas, the unstructured variance is too large compared to the structured variance to gain any additional information within a neighborhood. I recommend further research with variograms as a performance indicator for when adaptive sampling is likely to be effective for a population.

The Wilcoxon rank test showing no significant relationship between the bathymetry-parallel and bathymetry-perpendicular means was surprising since the clusters are elliptical (the bathymetry-perpendicular point estimates are ~0.19 km apart while the bathymetry-parallel estimates are ~1.9 km apart, ~0.2 km between in addition to the average 1.7 km tow length). Perhaps the difference in location on the parallel tows is approximately equivalent to the difference in depth on the perpendicular tows, or else it could have been that the catches were too variable and sample sizes too small to detect any difference.

The strong relationship between depth and CPUE provides further support that caution must be taken when utilizing abundance estimates from a broad range of habitat. The triennial survey clearly does not apply sufficient effort to these narrow depth intervals to precisely gauge abundance for POP (Lunsford 1999). It is evident that all three species examined are densely clustered in a small interval of depth and this information should be incorporated into any rockfish survey design.

Diel movement was evident from this study as the daytime means were much larger than the pure nighttime mean. This effect was from exceptionally large catches that occurred in the daytime. While this may not affect the adaptive sampling procedure itself because the criterion value is much lower than these catches, it could have a substantial effect on the estimates. The magnitude of this effect on estimation should be established in the future for ACS and conventional sampling.

As mentioned in the introduction of this thesis, sampling rockfish populations is problematic at best. Rockfish have a well-developed swim bladder that bursts upon rapid ascent to the surface during sampling (Balsiger et al. 1985). Thus, mark-recapture methods have not been developed for these species due to the difficulty of retrieving and returning at depth. For some years to come, trawl surveys will likely remain the optimum method of obtaining biomass estimates. Knowing this, future trawl surveys must be enhanced to better capture the true breadth of rockfish populations, particularly POP. Few fish species have such a large commercial value, with so little known about the true exploitable biomass. Since the current survey is not designed specifically to obtain precise estimates for these rockfish, insufficient sampling is conducted in their confined and clustered habitat. Adaptive cluster sampling may be one way to add additional samples in a cost-efficient manner. In the same way this research was conducted, a cost-recovery commercial vessel could be contracted to follow the NMFS survey and perform adaptive sampling on dense POP areas. Not only would this be an efficient way to add effort to POP estimates, but also it would ensure that the higher catches of POP are not discarded. For this to be successful, research into a preset criterion and net calibrations would be required. It might also be necessary to analyze the catches to determine the structure and density when ACS is efficient.

Additional methods to be explored involve using hydroacoustics in either conjunction with ACS or in a Trawl and Acoustic Presence/Absence Study (TAPAS) style of double sampling (Everson et al. 1996). The former would use hydroacoustic data to determine if a location has enough rockfish to exceed the criterion before trawling it, thus saving time spent on sampling edge units. The latter method, TAPAS, uses hydroacoustic information to delineate a low-density area and a high-density area, which are then utilized as a background stratum and a high-density stratum. Simulations and pilot studies should be performed to see if these methods hold promise for POP.

Rockfish are an ecologically and economically important constituent of Alaskan waters. We need to ensure that their stocks are managed in a conservative but lucrative way; to do this it is vital that we advance our knowledge of rockfish population size and structure. That road is not yet obvious, but the signs are clearer.

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Appendix I: Within-haul variation

(parts excerpted from Quinn et al. 1999)

The goal of this study is to estimate mean catch per unit of effort (CPUE), rockfish catch in weight divided by the total distance trawled. Let the initial sample size be n and the total number of sampling units (the total number of possible hauls) be N. For each haul i, a systematic subsample of the haul (second stage of sampling) was frequently taken, because the total haul could not be enumerated if the total haul catch exceeded one mt. The subsample was projected to the total sample using a ratio estimator (Cochran 1977, p.153), resulting in a first-stage estimate of rockfish catch, $\hat{y}_i$, and a within-haul variance estimate $v_2(\hat{y}_i)$ (Cochran 1977, eq.(6.13)). The weight w_i is known for every sample. For those hauls totally enumerated, the within-haul variance is set to zero. Suppose that an unbiased estimator of the first-stage mean for rockfish CPUE can be written as

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{n} w_i \hat{y}_i .$$

From Cochran (1977, p.300-302), an unbiased estimator of the variance is

$$v(\hat{\mu}) = v_1(\hat{\mu}) + \frac{1}{N^2}\sum_{i=1}^{n} w_i v_2(\hat{y}_i),$$

where $v_1(\hat{\mu})$ is the variance estimate that would be used if there were no subsampling. Specific formulae for simple random sampling and adaptive cluster sampling with within-haul variation are now given.

Simple random sampling (SRS)

$$\hat{\mu}_{\text{srs}} = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i = \frac{1}{N}\sum_{i=1}^{n}\frac{N}{n}\hat{y}_i;\text{ hence } w_i = \frac{N}{n}.$$

$$v(\hat{\mu}_{\text{srs}}) = \left(1-\frac{n}{N}\right)\frac{s_{\text{srs}}^2}{n} + \frac{1}{Nn}\sum_{i=1}^{n}v_2(\hat{y}_i),$$

the typical 2-stage cluster sampling formulae (Thompson 1992, p.129; Cochran 1977, p.303).

Hansen-Hurwitz estimator for adaptive cluster sampling (HH)

Let $\hat{y}_i^*$ be the sum of the $\hat{y}_{ij}$'s for the network intersecting unit i, x_i be the size of that network, and the variance for the total in the network be $v_2(\hat{y}_i^*) = \sum_j v_2(\hat{y}_{ij})$.

$$\hat{\mu}_{\text{HH}} = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{y}_i^*}{x_i} = \frac{1}{N}\sum_{i=1}^{n}\frac{N}{nx_i}\hat{y}_i^*;\text{ hence } w_i = \frac{N}{nx_i}.$$

$$v(\hat{\mu}_{\text{HH}}) = \left(1-\frac{n}{N}\right)\frac{s_{\text{w}}^2}{n} + \frac{1}{Nn}\sum_{i=1}^{n}\frac{v_2(\hat{y}_i^*)}{x_i},$$

in which s_{w}^2 is the empirical variance of the $\{\hat{y}_i^* / x_i\}$ (Thompson 1992, p.271).

Horvitz-Thompson estimator for adaptive cluster sampling (HT)

Let $\hat{y}_k^*$ be the sum of the $\hat{y}_{kj}$'s for the k^{th} distinct network in the sample, x_k be the size of that network, and the variance for the total in the network be $v_2(\hat{y}_k^*) = \sum_j v_2(\hat{y}_{kj})$. Let the inclusion probability for that network be α_k.

$$\hat{\mu}_{\mathrm{HT}} = \frac{1}{N}\sum_{k=1}^{\kappa}\frac{\hat{y}_k^*}{\alpha_k};\ \text{hence}\ w_k = \frac{1}{\alpha_k}.$$

$$v(\hat{\mu}_{\mathrm{HT}}) = \frac{1}{N^2}\sum_{k=1}^{\kappa}\sum_{h=1}^{\kappa}\frac{\hat{y}_k^*\hat{y}_h^*(\alpha_{kh}-\alpha_k\alpha_h)}{\alpha_k\alpha_h\alpha_{kh}} + \frac{1}{N^2}\sum_{k=1}^{\kappa}\frac{v_2(\hat{y}_k^*)}{\alpha_k},$$

in which κ is the number of distinct networks in the sample (Thompson 1992, p.274).

<u>Within-haul variance prediction</u>

In some instances, within-haul variance could become more than negligible in estimation. It might be useful to determine when within-haul variance can play an important role in the variance of estimates. A model was constructed to predict within-haul variance of the catch (rather than CPUE, for simplicity) for POP using nonlinear regression. Ninety-one subsampled hauls were used. The haul 160 outlier was removed. Five variables were originally considered: Total haul catch (corrected flow scale weight), total POP catch (kg), fraction of POP in the catch, number of subsamples, and the fraction of the total catch sampled. The full model with the lowest sum of squares was as follows:

$$W\hat{H}V = 1839.5\sqrt{PT} - 221.2\sqrt[4]{FS} - 76364.5\times PF - 466.8\times SN - 0.99\times SF$$

where $W\hat{H}V$ is the predicted within-haul variance, *PT* is the total POP caught, *FS* is the corrected flowscale weight, *PF* is the fraction of POP in the catch, *SN* is the number of subsamples and *SF* is the fraction of catch sampled. The sum of squares was equal to $8.53\text{x}10^{10}$. The fit to the data was good with 60% of the variance explained (Figure 19, p.60). When the outlier was included, the R^2 was higher (0.68) but the sum of squares was more than twice as high due to the high leverage that data point exhibited. To achieve parsimony, the significance of the parameter estimates was determined. Figure 20 (p.60) shows the effect of each of the top four parameters (omitting *SF* from the model) when the others are fixed at their average values for the cruise. This helps indicate the fact that only the *PT* and *PF* parameters were significant ($p<0.005$). The larger models were rejected until F-tests showed that a model using those two parameters was better than using only one of them to predict within-haul variance ($p<0.001$) yielding

$$W\hat{H}V = 1896.4\sqrt{PT} - 87873.9 \times PF$$

with both parameter estimates highly significant ($p<0.001$). The sum of squares for this model was 8.60×10^{10}. As one might guess, these parameter estimates are highly correlated ($r=0.95$). Figure 21 (p.61) shows how the within-haul variance prediction varies with each of these variables. When the fraction of POP in the catch is high, $W\hat{H}V$ is small. When the total POP catch increases, so does $W\hat{H}V$.

This model might be useful as a surrogate for within-haul variance when subsampling is not recorded in observer or catch data. Alternatively, it could be useful as an indicator of when an analyst needs to account for within-haul variance.

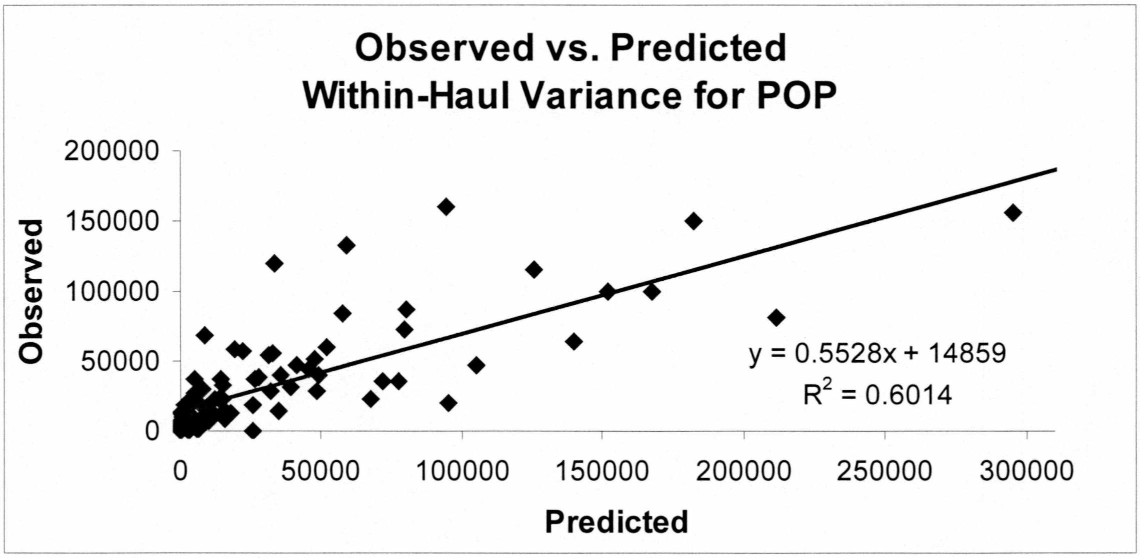

Figure 19. Within-haul variance prediction from the full model for Pacific ocean perch (POP) using nonlinear least squares.

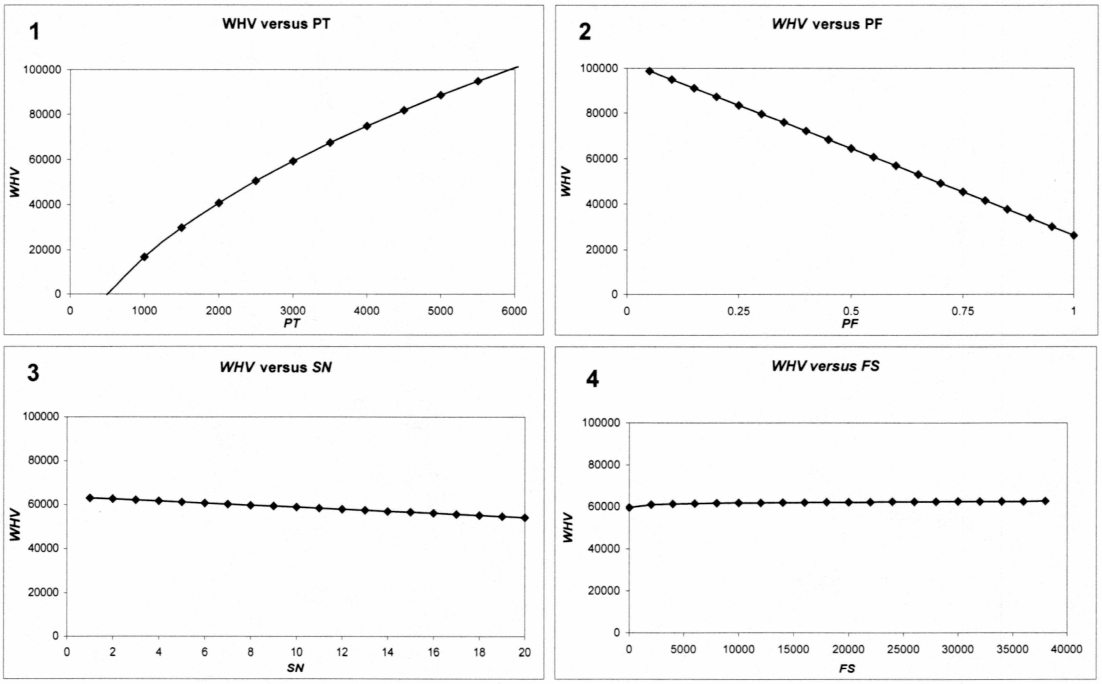

Figure 20. Effects of the top four (ordered left to right in terms of parameter significance) variables in within-haul variance model (WHV) when holding the other three at their cruise averages (*FS*=5092, *PF*=0.54, *SN*=4.6, *PT*=3126).

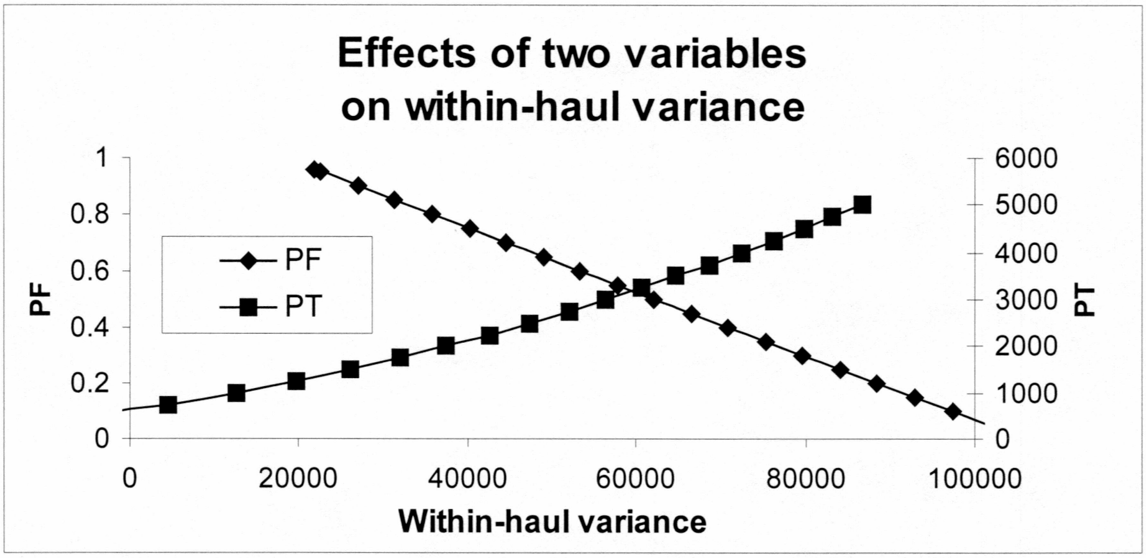

Figure 21. Effect on within-haul variance of holding one parameter at the cruise average (*PF*=0.54, *PT*=3126) while varying the other for the most parsimonious model.

Appendix II: Fishing operations and catch sampling

(excerpted from Clausen et al. 1999)

Fishing operations were conducted 24 hours a day; no attempt was made to account for possible day-night differences in catch rates. Duration of all trawl hauls was 15 minutes on bottom, measured from the time the net reached equilibrium on the bottom until the time that retrieval of the net began. Equilibrium time was based on the skipper's judgment as to when the net was on bottom and fishing properly. We chose 15 minutes to correspond with the standard duration of hauls during the triennial trawl surveys. In addition, tows of this relatively short duration were necessary in the experiment to determine more precisely the extent of rockfish concentrations in the adaptive phase. Vessel speed during the tows was approximately 6.5 km/h (3.5 knots), so that distance towed over the bottom was about 1.7 km (0.9 nm). During retrieval, vessel speed was approximately 1.9 km/h (1 kt) or less. On a few occasions, the gear snagged on the bottom and was retrieved early, resulting in a shorter distance towed.

Positioning for each tow was determined on a computer using SeaPlot navigational software linked to differential GPS. As much as possible, tows were in a straight line and generally followed a constant depth contour. For positioning the random stations, a list of random starting positions was compiled for each stratum. Originally, the direction of each random tow was chosen at random, but this created difficulties in placement of the adaptive tows when two random stations were close to each other. Subsequently, all tows in a stratum were made in the same direction. Because of the orientation of the contours, this tended to be approximately east or west in the POP study area, or approximately north or south in the shortraker-rougheye study area. For the adaptive stations, every effort was made to position the tows along the same heading as the random station they were associated with so that a symmetrical sampling network would result. In most cases, the skipper was able to do a good job of this, while also maintaining the planned distance of 0.19 km (0.1 nm) between all tows. The only exceptions occurred when strong currents or winds unexpectedly forced the vessel off course during a tow or caused the net to sink too fast or slowly; a few times, this resulted in two trawl paths crossing.

On a small number of tows, a SCANMAR net mensuration system, provided by the AFSC, was used to measure the width and height of the net opening. This equipment included acoustic sensors that attached to the net, a hydrophone deployed over the side of the vessel to receive data from the sensors, and a microcomputer system in the wheelhouse to interpret and store the data. A micro-bathythermograph (micro-BT) was also mounted on the net for a selected number of tows. This device recorded the time when the net reached and left bottom and provided a water temperature profile during the tow.

The vessel's Simrad ES 380 depth sounder was used to obtain a color printout of the bottom trace and fish sign associated with each tow, until the printer broke down about halfway through the cruise. To ensure comparability of all the printouts, all settings for the sounder were standardized at the beginning of the cruise, and they remained undisturbed for the duration of the cruise.

Catch Sampling

When the net was hauled aboard at the end of a tow, a scientist measured the dimensions of the codend with a tape measure to determine a volumetric estimate of the catch. The catch was then dumped through a hydraulic opening in the deck into the factory's "live tank." From the live tank, a conveyer belt transported the catch to either the scientific sampling area or the commercial processing line, where the fish were processed or discarded. Total weight of the catch for each haul was obtained from a Scanvaegt electronic flow scale (model Scanflow 4674/4600) that was mounted along the conveyer belt before the catch reached the sampling or processing areas. Accuracy of the scale was verified every 1–2 days using samples of known weight.

Catches less than approximately one metric ton (mt) were scientifically sampled in their entirety ("whole-haul" sampling). The catch was sorted by species, and each species was then weighed and counted according to standard AFSC and RACE Division protocol. A Marel motion-compensated platform scale, model M15, provided by the vessel, was used for all the scientific weighing, except for Pacific halibut (*Hippoglossus stenolepis*), which were measured individually for length, and a length-weight regression was used to determine their weight. This special procedure for Pacific halibut was followed to increase the survival of these fish, as all were released overboard soon after measurement. If available, a random subsample of 150 fish/species was taken for length measurements of POP, shortraker rockfish, rougheye rockfish and other abundant rockfish species in each haul. If less than 150 fish/species were caught, then all fish caught were measured. Sex was not determined for any of the fish measured because dissection necessary for the sexing would have disfigured the fish and lessened their commercial value. The length data were collected electronically with data loggers and barcode-based recording devices and downloaded later to computer database files. After all the scientific sampling was completed, the fish became property of the vessel for commercial processing or discard.

For catches greater than approximately one mt, five 100-kg subsamples were taken and sampled for species composition using procedures similar to those described above. The remainder of the catch went directly without sampling to commercial processing or discard. This subsampling scheme was determined by the NMFS fishery observer program for their study of within-haul variability of species composition. The 100-kg subsamples were selected systematically with a random starting point as the catch passed over the flow scale. In this manner, the subsamples were dispersed throughout the entire haul to reduce bias caused by possible species segregation in the net and live tank.

In some instances, we unintentionally ended up with only three or four subsamples from a haul when the catch weight turned out to be less than expected. The subsample data were later expanded over the weight of the haul's entire catch to yield estimates of the total catch composition. In addition, up to five randomly selected subsamples were made for some hauls, so that the observer program could later compare systematic subsampling to random subsampling.

The catch data had to be corrected from the original raw data because of errors in weight measurement by the flow scale. At sea, between hauls 61 and 107, we noticed that the flow scale sometimes registered catch weight even though no catch was passing over at that time. Testing the flow scale with known weights confirmed that the scale was overweighing the catch by an average of 5.87% during this period. Consequently, we have adjusted all the catches for hauls 61–107 downward by 5.87%. In addition, the remaining flow-scale tests when the scale was functioning normally indicated a slight tendency to overweigh (mean of all the tests showed the scale was over by 0.19%); hence, we adjusted the catches for hauls 1–60 and 108–190 downward by 0.19%.

Appendix III: Data summary used in results.

Haul	Station	Lat	Long	POP Corrected CPUE	POP Within-haul variance	SR/RE Corrected CPUE	SR/RE Within-haul variance	Tow Type	Stratum
3	84	57.84	-149.58	897.0	4582	168.2	589	Random-POP	Slope
4	91	57.88	-149.59	302.9	8450	0.3	0	Random-POP	Slope
5	90	57.84	-149.67	1195.6	6121	38.2	81	Random-POP	Slope
6	76	57.82	-149.70	234.8	0	40.7	0	Random-POP	Slope
7	86	57.87	-149.68	137.5	0	7.1	0	Random-POP	Slope
8	87	57.82	-149.83	75.0	0	1.4	0	Random-POP	Slope
9	85	57.89	-149.85	19.5	0	1.7	0	Random-POP	Slope
10	81	57.84	-149.91	5.3	0	2.1	0	Random-POP	Slope
11	82	57.78	-149.89	13.5	0	0.4	0	Random-POP	Slope
12	79	57.69	-149.96	187.1	0	9.9	0	Random-POP	Slope
13	77	57.66	-150.03	80.7	0	6.8	0	Random-POP	Slope
14	83	57.70	-150.08	91.2	0	2.5	0	Random-POP	Slope
15	80	57.59	-150.13	39.8	0	49.1	0	Random-POP	Slope
16	78	57.63	-150.25	131.9	0	15.9	0	Random-POP	Slope
17	88	57.68	-150.21	6.0	0	0.0	0	Random-POP	Slope
18	84-2	57.84	-149.55	293.0	995	35.1	40	Adaptive-POP	Slope
19	84-1	57.82	-149.62	416.3	1604	460.8	12541	Adaptive-POP	Slope
20	84-4	57.85	-149.53	138.8	0	18.4	0	Adaptive-POP	Slope
21	84-3	57.81	-149.65	2423.1	149179	1274.1	43339	Adaptive-POP	Slope
22	84-5	57.81	-149.68	218.2	2105	167.5	709	Adaptive-POP	Slope
23	-	57.82	-149.67	0.0	5849	0.0	1172	Invalid	—
24	91-1	57.89	-149.65	651.4	14135	0.0	0	Adaptive-POP	Slope
25	91-2	57.89	-149.55	761.3	1777	0.0	0	Adaptive-POP	Slope
26	91-4	57.89	-149.52	123.3	0	0.0	0	Adaptive-POP	Slope
27	91-3	57.89	-149.69	226.8	0	1.3	0	Adaptive-POP	Slope
28	90-1	57.84	-149.70	996.4	6113	64.6	548	Adaptive-POP	Slope
29	90-2	57.84	-149.62	284.5	0	26.5	0	Adaptive-POP	Slope
30	90-3	57.84	-149.73	138.4	0	11.4	0	Adaptive-POP	Slope
31	90-4	57.84	-149.60	720.9	3120	7.8	2	Adaptive-POP	Slope
32	90-6	57.84	-149.58	228.6	478	6.4	5	Adaptive-POP	Slope
33	1	57.87	-150.16	179.2	0	0.0	0	Random-POP	Intersection
34	2	57.85	-150.10	250.8	0	2.4	0	Random-POP	Intersection
35	3	57.87	-150.06	104.6	0	0.0	0	Random-POP	Intersection
36	4	57.84	-149.99	167.8	0	1.5	0	Random-POP	Intersection
37	9	57.80	-149.98	1615.9	17583	2.2	4	Random-POP	Intersection
38	10	57.82	-149.95	53.9	0	0.0	0	Random-POP	Intersection
39	8	57.81	-150.05	44.6	0	0.8	0	Random-POP	Intersection
40	7	57.81	-150.10	29.0	0	0.0	0	Random-POP	Intersection
41	6	57.80	-150.16	58.6	0	0.0	0	Random-POP	Intersection
42	11	57.84	-150.15	27.6	0	0.0	0	Random-POP	Intersection

Haul	Station	Lat	Long	POP Corrected CPUE	POP Within-haul variance	SR/RE Corrected CPUE	SR/RE Within-haul variance	Tow Type	Stratum
43	16	57.75	-150.18	67.6	0	0.0	0	Random-POP	Intersection
44	12	57.77	-150.14	14.6	0	0.0	0	Random-POP	Intersection
45	13	57.78	-150.10	14.9	0	0.0	0	Random-POP	Intersection
46	14	57.78	-150.01	2914.8	40842	1.4	2	Random-POP	Intersection
47	15	57.76	-149.97	6288.7	46628	0.0	0	Random-POP	Intersection
48	15-2	57.76	-149.98	9139.8	80337	0.0	0	Adaptive-POP	Intersection
49	15-3	57.76	-149.93	2319.3	15359	2.4	2	Adaptive-POP	Intersection
50	15-4	57.76	-149.97	542.8	1785	1.5	1	Adaptive-POP	Intersection
51	15-1	57.77	-150.00	4841.0	50909	0.0	0	Adaptive-POP	Intersection
52	15-7	57.76	-149.97	258.3	3668	2.2	1	Adaptive-POP	Intersection
53	15-8	57.76	-149.93	2265.8	14464	3.8	10	Adaptive-POP	Intersection
54	15-10	57.75	-149.92	2055.6	10216	3.1	4	Adaptive-POP	Intersection
55	15-11	57.76	-149.97	2021.0	18559	0.0	0	Adaptive-POP	Intersection
56	15-12	57.77	-150.01	1202.6	18452	0.0	0	Adaptive-POP	Intersection
57	15-5	57.77	-150.03	174.3	0	0.0	0	Adaptive-POP	Intersection
58	15-6	57.77	-149.99	946.7	959	3.5	4	Adaptive-POP	Intersection
59	15-17	57.76	-149.92	3289.5	8374	4.7	10	Adaptive-POP	Intersection
60	15-21	57.75	-149.92	7372.2	14439	15.3	228	Adaptive-POP	Intersection
61	15-22	57.75	-149.95	1164.5	18926	0.0	0	Adaptive-POP	Intersection
62	15-23	57.76	-150.00	824.4	2873	0.5	0	Adaptive-POP	Intersection
63	15-24	57.77	-150.04	880.8	1079	0.0	0	Adaptive-POP	Intersection
64	15-14	57.77	-150.02	4257.4	48713	0.0	0	Adaptive-POP	Intersection
65	15-15	57.77	-150.00	8166.9	29986	0.0	0	Adaptive-POP	Intersection
66	14-2	57.78	-150.00	1130.5	7984	0.0	0	Adaptive-POP	Intersection
67	14-3	57.77	-149.95	4967.3	49686	0.0	0	Adaptive-POP	Intersection
68	14-4	57.77	-150.01	385.0	1840	0.3	0	Adaptive-POP	Intersection
69	14-1	57.79	-150.04	817.3	4754	0.0	0	Adaptive-POP	Intersection
70	14-7	57.78	-150.00	9793.1	121684	0.0	0	Adaptive-POP	Intersection
71	14-8	57.77	-149.96	3772.9	4118	0.0	0	Adaptive-POP	Intersection
72	14-9	57.76	-149.93	1493.7	3648	7.5	5	Adaptive-POP	Intersection
73	14-12	57.78	-150.03	761.7	0	2.0	0	Adaptive-POP	Intersection
74	14-6	57.79	-150.03	1608.3	25011	0.0	0	Adaptive-POP	Intersection
75	14-5	57.79	-150.07	147.5	0	0.2	0	Adaptive-POP	Intersection
76	14-16	57.79	-150.00	2040.5	10230	0.0	0	Adaptive-POP	Intersection
77	14-17	57.70	-149.96	4501.5	21798	10.3	101	Adaptive-POP	Intersection
78	14-18	57.77	-149.93	3153.7	13917	1.2	1	Adaptive-POP	Intersection
79	14-23	57.78	-150.03	259.8	345	0.4	0	Adaptive-POP	Intersection
80	14-24	57.79	-150.06	28.1	0	0.0	0	Adaptive-POP	Intersection
81	14-14	57.79	-150.06	49.1	0	0.4	0	Adaptive-POP	Intersection
82	14-15	57.79	-150.02	313.6	0	0.5	0	Adaptive-POP	Intersection
83	9-1	57.79	-150.01	1791.2	6748	0.0	2	Adaptive-POP	Intersection
84	9-2	57.80	-149.99	1613.9	18578	0.0	0	Adaptive-POP	Intersection
85	9-3	57.80	-149.94	64.7	0	0.0	0	Adaptive-POP	Intersection
86	9-4	57.80	-149.99	1294.2	3404	4.2	4	Adaptive-POP	Intersection
87	9-12	57.79	-150.02	1732.1	19686	1.1	1	Adaptive-POP	Intersection
88	9-6	57.80	-150.01	10117.7	41487	0.0	0	Adaptive-POP	Intersection

				POP		SR/RE			
Haul	Station	Lat	Long	Corrected CPUE	Within-haul variance	Corrected CPUE	Within-haul variance	Tow Type	Stratum
89	9-7	57.81	-149.99	3080.5	20005	0.7	0	Adaptive-POP	Intersection
90	9-8	57.82	-149.95	335.1	0	0.4	0	Adaptive-POP	Intersection
91	9-10	57.81	-149.95	387.6	0	0.5	0	Adaptive-POP	Intersection
92	9-11	57.79	-149.99	1019.7	7692	3.8	3	Adaptive-POP	Intersection
93	9-23	57.79	-150.02	840.4	7900	7.3	14	Adaptive-POP	Intersection
94	9-14	57.79	-150.03	2626.5	27761	0.0	0	Adaptive-POP	Intersection
95	9-15	57.80	-150.02	1898.8	8796	6.2	19	Adaptive-POP	Intersection
96	9-16	57.81	-149.99	1036.6	34671	0.0	0	Adaptive-POP	Intersection
97	9-21	57.81	-149.94	95.8	0	0.0	0	Adaptive-POP	Intersection
98	9-22	57.80	-149.97	208.5	0	2.8	0	Adaptive-POP	Intersection
99	34	57.91	-150.18	40.3	0	0.0	0	Random-POP	WestGully
100	41	57.98	-150.13	16.4	0	0.0	0	Random-POP	WestGully
101	35	58.00	-150.25	292.5	2956	0.0	0	Random-POP	WestGully
102	31	58.02	-150.23	65.1	1042	0.0	0	Random-POP	WestGully
103	267	58.05	-150.19	8.6	73	0.0	0	Random-POP	WestGully
104	37	58.04	-150.24	1123.7	15220	0.0	0	Random-POP	WestGully
105	30	58.10	-150.25	36.6	701	0.0	0	Random-POP	WestGully
106	31	58.12	-150.25	3.3	11	0.0	0	Random-POP	WestGully
107	32	58.14	-150.38	158.4	0	0.6	0	Random-POP	WestGully
108	29	58.12	-150.43	139.5	554	3.4	10	Random-POP	WestGully
109	39	58.10	-150.41	92.3	0	0.0	0	Random-POP	WestGully
110	36	58.10	-150.51	52.4	0	1.0	0	Random-POP	WestGully
111	27	58.09	-150.55	214.5	0	0.0	0	Random-POP	WestGully
112	33	58.01	-150.54	45.6	0	0.0	0	Random-POP	WestGully
113	40	57.96	-150.38	117.0	0	0.0	0	Random-POP	WestGully
114	37-3	58.04	-150.23	153.5	1737	0.0	0	Adaptive-POP	WestGully
115	37-4	58.04	-150.25	1022.3	40518	0.0	0	Adaptive-POP	WestGully
116	37-1	58.07	-150.28	81.6	0	0.0	0	Adaptive-POP	WestGully
117	37-2	58.05	-150.24	62.2	0	0.0	0	Adaptive-POP	WestGully
118	37-10	58.03	-150.23	0.0	0	0.0	0	Adaptive-POP	WestGully
119	37-11	58.04	-150.25	4.1	6	0.0	0	Adaptive-POP	WestGully
120	37-12	58.06	-150.29	2.5	2	0.0	0	Adaptive-POP	WestGully
121	35-1	58.02	-150.27	28.1	68	0.0	0	Adaptive-POP	WestGully
122	35-2	57.99	-150.24	15.2	10	0.0	0	Adaptive-POP	WestGully
123	35-3	57.98	-150.23	6.7	0	0.0	0	Adaptive-POP	WestGully
124	35-4	57.99	-150.25	92.7	906	0.0	0	Adaptive-POP	WestGully
125	58	58.05	-150.13	10.3	0	0.0	0	Random-POP	EastGully
126	51	58.01	-150.11	10.7	0	0.0	0	Random-POP	EastGully
127	61	57.95	-150.05	19.2	0	3.8	0	Random-POP	EastGully
128	55	57.92	-149.92	64.7	0	4.6	0	Random-POP	EastGully
129	59	57.99	-149.94	34.0	0	1.1	0	Random-POP	EastGully
130	53	58.04	-149.95	24.5	0	3.7	0	Random-POP	EastGully
131	60	57.98	-149.81	496.2	0	2.1	0	Random-POP	EastGully
132	56	58.03	-149.82	1378.2	2994	0.0	0	Random-POP	EastGully
133	62	58.07	-149.82	61.2	0	7.6	0	Random-POP	EastGully
134	54	58.14	-149.88	37.9	0	0.4	0	Random-POP	EastGully

Haul	Station	Lat	Long	POP Corrected CPUE	POP Within-haul variance	SR/RE Corrected CPUE	SR/RE Within-haul variance	Tow Type	Stratum
135	52	58.11	-150.05	14.1	0	0.7	0	Random-POP	EastGully
136	57	58.14	-150.18	140.0	1957	0.0	0	Random-POP	EastGully
137	56-4	58.03	-149.83	2032.7	21354	1.8	3	Adaptive-POP	EastGully
138	56-1	58.05	-149.86	66.0	0	0.9	0	Adaptive-POP	EastGully
139	56-2	58.03	-149.82	349.9	3724	1.5	1	Adaptive-POP	EastGully
140	56-3	58.02	-149.80	261.4	0	0.0	0	Adaptive-POP	EastGully
141	56-11	58.02	-149.83	1093.8	2947	0.5	0	Adaptive-POP	EastGully
142	56-12	58.05	-149.87	56.2	0	4.2	0	Adaptive-POP	EastGully
143	56-6	58.05	-149.85	9.2	0	8.4	0	Adaptive-POP	EastGully
144	56-7	58.03	-149.81	84.4	0	2.2	0	Adaptive-POP	EastGully
145	56-8	58.02	-149.79	310.6	0	1.1	0	Adaptive-POP	EastGully
146	56-9	58.00	-149.77	73.5	0	0.0	0	Adaptive-POP	EastGully
147	56-10	58.01	-149.80	1005.5	0	0.0	0	Adaptive-POP	EastGully
148	56-22	58.02	-149.83	1804.6	3114	0.0	0	Adaptive-POP	EastGully
149	56-23	58.04	-149.88	72.7	0	7.0	0	Adaptive-POP	EastGully
150	56-20	58.00	-149.78	499.0	0	0.4	0	Adaptive-POP	EastGully
151	56-21	58.01	-149.81	1329.0	1187	0.0	0	Adaptive-POP	EastGully
152	110	58.92	-148.09	53.3	693	132.6	8095	Random-SR/RE	SR/RE North
153	116	58.86	-148.17	3.4	0	285.1	0	Random-SR/RE	SR/RE North
154	123	58.81	-148.19	9.9	0	366.6	0	Random-SR/RE	SR/RE North
155	113	58.76	-148.17	23.6	57	1475.5	10233	Random-SR/RE	SR/RE North
156	103	58.74	-148.16	19.9	0	534.7	0	Random-SR/RE	SR/RE North
157	118	58.77	-148.18	25.2	25	1758.0	15797	Random-SR/RE	SR/RE North
158	101	58.81	-148.21	0.0	34263	1048.4	24329	Random-SR/RE	SR/RE North
159	124	58.86	-148.19	782.9	29765	1145.5	37058	Random-SR/RE	SR/RE North
160	T3	58.83	-148.21	24532.6	492822	269.2	182286	Random-SR/RE	SR/RE North
161	115	58.89	-148.16	8.9	57	644.1	18333	Random-SR/RE	SR/RE North
162	T5	58.90	-148.13	0.0	0	0.0	0	Invalid	—
163	114	58.94	-148.07	20.4	172	1115.5	5897	Random-SR/RE	SR/RE North
164	T4	58.95	-148.04	0.0	0	143.1	0	Random-SR/RE	SR/RE North
165	118-1	58.79	-148.19	166.6	1340	899.3	7281	Adaptive-SR/RE	SR/RE North
166	118-2	58.75	-148.18	59.1	530	4246.1	148860	Adaptive-SR/RE	SR/RE North
167	118-4	58.73	-148.17	11.0	75	4297.9	46114	Adaptive-SR/RE	SR/RE North
168	118-6	58.72	-148.18	26.3	82	2838.8	23685	Adaptive-SR/RE	SR/RE North
169	113-1	58.78	-148.18	5.3	0	369.6	0	Adaptive-SR/RE	SR/RE North
170	113-2	58.73	-148.17	0.0	0	3472.4	0	Adaptive-SR/RE	SR/RE North
171	113-4	58.72	-148.18	29.9	473	4759.8	30448	Adaptive-SR/RE	SR/RE North
172	119	58.62	-148.36	1.6	0	405.3	0	Random-SR/RE	SR/RE South
173	125	58.56	-148.43	5.6	0	478.9	0	Random-SR/RE	SR/RE South
174	108	58.52	-148.47	1.1	0	353.0	0	Random-SR/RE	SR/RE South
175	S9	58.52	-148.47	0.0	0	61.7	0	Random-SR/RE	SR/RE South
176	S3	58.47	-148.51	10.0	0	107.0	0	Random-SR/RE	SR/RE South
177	109	58.44	-148.48	0.0	0	836.7	8965	Random-SR/RE	SR/RE South
178	120	58.41	-148.51	15.8	0	192.2	0	Random-SR/RE	SR/RE South
179	S1	58.36	-148.52	4.3	0	85.3	0	Random-SR/RE	SR/RE South
180	S4	58.32	-148.53	0.0	0	481.7	0	Random-SR/RE	SR/RE South

Haul	Station	Lat	Long	POP Corrected CPUE	POP Within-haul variance	SR/RE Corrected CPUE	SR/RE Within-haul variance	Tow Type	Stratum
181	121	58.32	-148.55	45.1	0	158.9	0	Random-SR/RE	SR/RE South
182	S5	58.26	-148.63	14.5	0	180.6	0	Random-SR/RE	SR/RE South
183	S12	58.23	-148.73	2.2	0	1.8	0	Random-SR/RE	SR/RE South
184	109-1	58.46	-148.50	3.1	0	86.0	0	Adaptive-SR/RE	SR/RE South
185	109-2	58.41	-148.50	1.5	0	172.2	0	Adaptive-SR/RE	SR/RE South
186	Paul1	58.72	-148.18	46.5	358	3814.6	46758	Test	—
187	Paul2	58.72	-148.18	70.2	51	2393.8	35283	Test	—
188	119-1	58.63	-148.35	2.0	0	437.0	0	Adaptive-SR/RE	SR/RE South
189	119-2	58.59	-148.40	2.7	0	489.5	0	Adaptive-SR/RE	SR/RE South
190	119-4	58.58	-148.41	4.7	0	197.8	0	Adaptive-SR/RE	SR/RE South

Appendix IV: Rao-Blackwell Improvement

Based on using the sufficient statistic of the sample, the adaptive estimators can be improved by incorporating information from the edge units (Thompson 1992, Thompson and Seber 1996, Salehi 1999). In short, this is done by narrowing the data to the unordered set of network values and edge units, and then averaging across all possible ways the sample could have occurred. Unfortunately, when there are only one or two networks that are sampled, no improvement in precision can be gained for the HT estimator due to the statistical properties of the intersection probabilities. When there is only one network, the RB improvement of the HH estimator is not useful either. Since the east gully stratum has only one network, it is not presented.

Applying the Rao-Blackwell improvement showed interesting results (Table 6, p.72). First, similar to results in Salehi (1999), the RB versions of the HT standard errors show little improvement in either of the three-network strata. The other three strata had only two networks, so the RB improvement of the HT estimator could not be performed. As expected from Salehi (1999), the RB version of the HH estimators showed better gains in precision. In the slope stratum there was a slight decrease in the standard error. In the intersection stratum, the mean and standard error estimates decreased slightly. The mean decreases slightly in the direction of the HT estimate. The West Gully and SR/RE N strata showed the most marked decreases in standard error (~15%, Table 6). Finally, the SR/RE S showed a slight decrease in variance.

The results suggest that the effectiveness of the RB improvement may decrease as the amount of adaptive sampling occurs for POP, but there was not enough contrast in the small sample size for SR/RE to discern any relationship (Figure 22). An obvious caveat is that the POP relationship is based on only a few points. The overall results indicate that the Rao-Blackwell improvement does not ensure significant gains in precision, but can be useful in some cases.

Table 6. Comparison of estimates with Rao-Blackwell (RB) improvement versus standard adaptive estimators for all strata except the east gully due to it only having one network. "N/A" means that the RB versions of the HT estimator were not useful for these strata because they had only two networks.

	HT	HT_RB	HH	HH_RB
Slope				
μ	227.1	227.1	226.7	226.7
SE	80.4	80.4	80.4	75.8
CV	35.4%	35.4%	35.4%	33.4%
Intersection				
μ	251.5	251.5	600.1	590.3
SE	173.1	173.0	276.0	265.9
CV	68.8%	68.8%	46.0%	45.0%
W. Gully				
μ	157.1	N/A	157.1	157.1
SE	68.7	N/A	68.7	58.6
CV	43.7%	N/A	43.7%	37.3%
SR/RE N				
μ	1018.1	N/A	1017.2	1017.2
SE	319.9	N/A	320.0	268.7
CV	31.4%	N/A	31.5%	26.4%
SR/RE S				
μ	279.0	N/A	278.9	278.9
SE	69.5	N/A	69.5	67.6
CV	24.9%	N/A	24.9%	24.2%

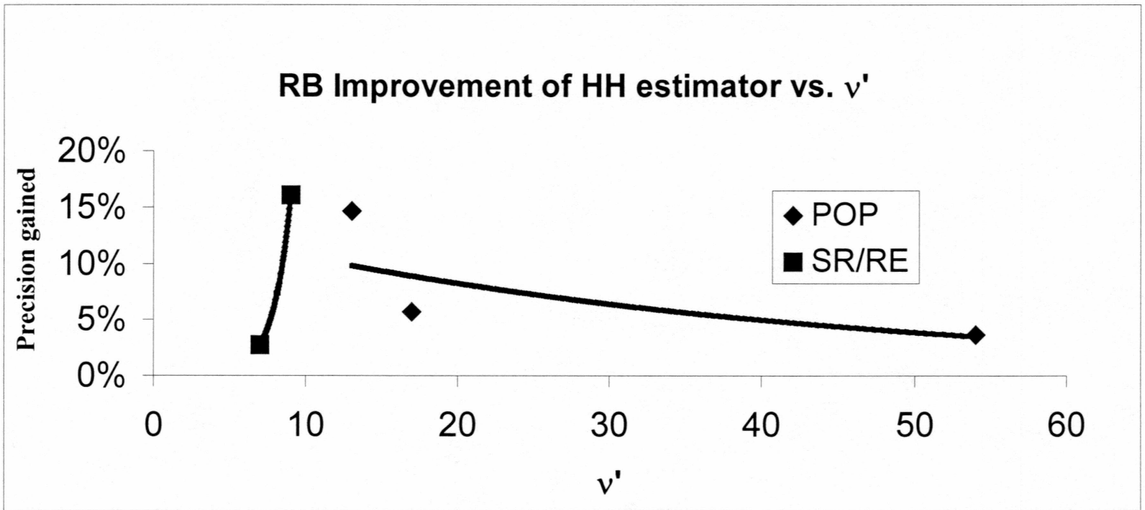

Figure 22. Comparison of improvement in precision (using standard error) as a function of ν' for Pacific ocean perch (POP) and shortraker/rougheye (SR/RE).